Barriers to Reallocation and Economic Growth: the Effects of Firing Costs*

Toshihiko Mukoyama
University of Virginia
tm5hs@virginia.edu

Sophie Osotimehin
University of Virginia
sophie.osotimehin@virginia.edu

May 2017

Abstract

We study how factors that hinder the reallocation of inputs across firms influence aggregate productivity growth. We extend Hopenhayn and Rogerson's (1993) general equilibrium firm dynamics model to allow for endogenous innovation. We calibrate the model using the US data, and then evaluate the effects of firing taxes on reallocation, innovation, and aggregate productivity growth. In our baseline specification, we find that firing taxes reduce overall innovation and productivity growth. We also find that firing taxes can have opposite effects on the entrants' innovation and the incumbents' innovation.

Keywords: Innovation, R&D, Reallocation, Firing costs
JEL Classifications: E24, J24, J62, O31, O47

*We thank seminar and conference participants at Canadian Economic Association Meetings, Econometric Society World Congress, Federal Reserve Board, Georgetown University, GRIPS, Hitotsubashi University, Midwest Macro Conference, Penn State, UQAM, Cornell, Michigan University, George Washington University, Southern Economic Association Meetings, and the UVa-Richmond Fed Research Jamboree for useful comments and suggestions. We also thank the Bankard Fund for Political Economy for financial support. We thank Meltem Poyraz and Diego Legal-Cañisá for excellent research assistance. All errors are ours.

1 Introduction

Recent empirical studies have underlined the existence of large flows of productive resources across firms and their important role for aggregate productivity. Production inputs are constantly being reallocated as firms adjust to changing market environments and new products and techniques are developed. As documented recently by Micco and Pagés (2007) and Haltiwanger et al. (2014), labor market regulations may dampen this reallocation of resources. Using cross-country industry-level data, these studies show that restrictions on hiring and firing reduce the pace of job creation and job destruction. In a similar vein, Davis and Haltiwanger (2014) find that the introduction of common-law exceptions that limit firms' ability to fire their employees at will has a negative impact on job reallocation in the United States.

The objective of this paper is to study the implications of firing regulations for aggregate productivity growth. By reducing job reallocation across firms, firing costs may affect not only the level of aggregate productivity but they are also likely to modify the incentives of firms to innovate. We investigate the consequences of firing costs on job reallocation and productivity growth using a model of innovation-based economic growth. We extend Hopenhayn and Rogerson's (1993) model of firm dynamics by introducing an innovation decision. Firms can invest in research and development (R&D) and improve the quality of products. Hence, in contrast to Hopenhayn and Rogerson's (1993) model (and the Hopenhayn (1992) model that it is based on) where the productivity process is entirely exogenous, job creation and job destruction in our model are the result of both idiosyncratic exogenous productivity shocks and *endogenous* innovation.

Following the seminal work of Grossman and Helpman (1991) and Aghion and Howitt (1992), we model innovation as a process of *creative destruction*: entrants displace the incumbent producers when they successfully innovate on an existing product. In addition to this Schumpeterian feature, we incorporate the innovations developed by incumbent firms. We allow incumbent firms to invest in R&D to improve the quality of their own product. The model is parsimonious and can be characterized analytically in the absence of firing costs. In particular, we show how the innovation rate of entrants and incumbents shape the growth rate of the economy and the firm size distribution. The frictionless model highlights the crucial role of reallocation for economic growth. As products of higher quality are introduced into the market, labor is reallocated towards these high-quality firms.[1] By limiting the reallocation of labor across firms, firing costs change the

[1]Aghion and Howitt (1994) is an earlier study that highlight this aspect of the Schumpeterian growth models in their analysis of unemployment.

firms' incentives to innovate and hence the growth rate of the economy.

We model employment protection as a firing tax and study its effect on innovation and growth. We find that the effects of the firing tax on aggregate productivity growth depend on the interaction between the innovation of entrants and incumbents. In fact, the firing tax can have opposite effects on entrants' and incumbents' innovation: while the firing tax tends to reduce entrants' innovation, it may raise the innovation incentives of incumbent firms. The firing tax reduces the entrants' innovation because the tax itself represents an additional cost that reduces expected future profits (direct effect). In addition, the misallocation of labor further reduces expected future profits (misallocation effect). For incumbents, the consequences of the firing tax are less clear-cut. In particular, the firing tax has an ambiguous impact on the incumbents' incentive to innovate. Firms that are larger than their optimal size have additional incentives to invest in R&D in the presence of the firing tax. For those firms, innovation has the added benefit of allowing them to avoid paying the firing tax as they would no longer need to downsize if the quality of their product is higher (tax-escaping effect). By contrast, for firms that are smaller than their optimal size, the direct effect and the misallocation effect tend to discourage innovation. In addition, the incumbents' incentive to innovate is affected by the rate at which entrants innovate. By reducing the entry rate, firing costs lower the incumbent's probability of being taken over by an entrant. This decline in the rate of creative destruction raises the expected return of R&D investments and therefore tends to raise the incumbents' innovation (creative-destruction effect). In our baseline calibration, the entrants' innovation rate falls and the incumbents' innovation rate rises as a result of the firing tax.[2] Overall, the negative effect on entrants dominates, and the firing tax leads to a fall in the rate of growth of aggregate productivity. Our results illustrate the importance of including the incumbents' innovation in the analysis: the fall in the growth rate is dampened by the response of the incumbents' innovation, and ignoring this dimension would have led to overestimate the decline in the growth rate. This result has implications beyond the study of firing costs. Regulations or market imperfections that reduce the entry rate are likely to have a weaker impact on growth once the incumbents' innovation is accounted for.

The negative effect of the firing tax on growth suggested by the baseline calibration is in line with recent empirical evidence on the topic. Firing regulations have been

[2] Saint-Paul (2002) makes a related argument that countries with a rigid labor market tend to produce relatively secure goods at a late stage of their product life cycle, so that these countries tend to specialize in 'secondary' innovations. A country with a more flexible labor market tends to specialize in 'primary' innovations. Thus increasing firing costs may encourage 'secondary' innovations, and the effect on aggregate growth depends on which type of innovation is more important.

shown to have a negative effect on the level but also on the growth rate of aggregate productivity.[3] Bassanini et al. (2009) find that firing costs tend to reduce total factor productivity growth in industries where firing costs are more likely to be binding. Using an empirical strategy similar to Bassanini et al. (2009), we complement our theoretical results by empirically investigating the effects of firing costs on R&D spending. We find, in line with the predictions of our baseline model, that firing costs tend to reduce R&D spending.

Our paper is related to several theoretical studies that study the consequences of firing costs on aggregate productivity. The existing literature, however, has mainly focused on the effects of firing costs on the *level* of aggregate productivity. Using a general equilibrium model of firm dynamics, Hopenhayn and Rogerson (1993) and more recently Moscoso Boedo and Mukoyama (2012) and Da-Rocha et al. (2016) have shown that firing costs hinder job reallocation and reduce allocative efficiency and aggregate productivity.[4] In line with these papers, we find that the *level* of employment and labor productivity falls. We show that in addition to the level effects, employment protection also affects the *growth rate* of aggregate productivity.

In focusing on the consequences of barriers to labor reallocation on aggregate productivity growth, our analysis goes one step beyond the recent literature on misallocation that focuses on the level effects, following the seminal work of Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). Empirical studies that evaluate the contribution of reallocation to productivity changes, such as Foster et al. (2001) and Osotimehin (2016), are designed to analyze the sources of productivity growth, rather than the level; in that sense, our analysis is more comparable to that literature. We highlight the fact that barriers to reallocation affect not only the allocation of resources across firms with different productivity levels, but also the productivity *process* itself as it modifies the firms' incentives to innovate. The additional effect of barriers to reallocation when productivity is endogenous is also the focus of Gabler and Poschke (2013) and Bento and Restuccia (forthcoming).[5] In contrast to our study, their focus is, as in the studies cited above,

[3]See Autor et al. (2007) for an estimate of how common-law restriction that limits firms' ability to fire (the "good faith exception") in the US had a detrimental effect on state total factor productivity in manufacturing.

[4]Hopenhayn and Rogerson (1993) find that a firing cost that amounts to one year of wages reduces aggregate total factor productivity by 2%. Moscoso Boedo and Mukoyama (2012) consider a wider range of countries, and show that firing costs calibrated to match the level observed in low income countries can reduce aggregate total factor productivity by 7%. Da-Rocha et al. (2016) analyzes a stylized continuous-time model where firm-level employment can only take two different values, and also find that the firing cost reduces aggregate productivity.

[5]In Gabler and Poschke (2013), firms grow by engaging in risky experimentation, and firing costs lead to a small *increase* in experimentation. Bento and Restuccia (forthcoming) show that policy distortions

exclusively on the level of aggregate productivity. Samaniego (2006*b*) highlights the effects of firing costs in a model with productivity growth. However, he considers only exogenous productivity growth and studies how the effects of firing costs differ across industries.[6] Poschke (2009) is one of the few exceptions that studies the effects of firing costs on aggregate productivity growth. In Poschke (2009), firing costs act as an exit tax which lowers the exit rate of low productivity firms. We focus on a different channel and show that firing costs may also affect aggregate productivity growth through their effects on R&D and innovation.[7]

Our paper is also related to the growing literature on innovation and firm-dynamics that followed the contribution by Klette and Kortum (2004). In particular, our paper is related to Acemoglu et al. (2013) that study the consequences of R&D subsidies and the allocation of R&D workers across firms. By contrast, our paper studies the effect of the allocation of production workers across firms. Also related are models by Akcigit and Kerr (2015), Acemoglu and Cao (2015), and Peters (2016) that consider quality-ladder firm dynamics models where incumbents are allowed to innovate on their own products.[8] Our model also exhibits this feature but focuses on a distinct question. Compared to these models, one important difference of our approach is that we use labor market data to discipline the model parameters, consistently with our focus on labor market reallocation and labor market policy.[9] Methodologically, these models are typically written in continuous time, while we use a discrete-time framework.[10] This modeling strategy allows us to solve the model with firing taxes using a similar method to those used for standard heterogeneous-agent models (such as Huggett (1993) and Aiyagari (1994)) and standard firm-dynamics models (such as Hopenhayn and Rogerson (1993) and Lee and Mukoyama (2008)). This is particularly important for our model, since firing taxes introduce a kink in the return function and makes it difficult to fully characterize the model analytically. The solution method also allows us to easily extend the model and to introduce several features that improve the fit of the model.

that are positively correlated to establishment-level productivity imply larger reductions in aggregate productivity when productivity is endogenous.

[6]He finds that firing costs have a stronger negative impact in industries where the rate of technical change is rapid. In a related paper, Samaniego (2008) finds that the increase in aggregate employment induced by embodied technical change is smaller in the presence of firing costs.

[7]Bertola (1991) is an earlier paper that analyzes the growth effect of firing costs. His analysis is mostly qualitative.

[8]Earlier papers that analyze incumbents' innovations in the quality-ladder framework include Segerstrom and Zolnierek (1999), Aghion et al. (2001), and Mukoyama (2003).

[9]Garcia-Macia et al. (2015) also utilizes labor market data to quantify their model, innovation is however exogenous in their model.

[10]Ates and Saffie (2016) is another recent contribution based on a discrete-time formulation of the Klette-Kortum model.

The paper is organized as follows. Section 2 sets up the model. Section 3 provides analytical characterizations of the model. Section 4 describes the quantitative analysis. Section 5 analyzes two extensions of the baseline model. Section 6 presents some empirical evidence on the relationship between firing costs and R&D. Section 7 concludes.

2 Model

We build a model of firm dynamics in the spirit of Hopenhayn and Rogerson (1993). We extend their framework to allow for endogenous productivity at the firm level. The innovation process is built on the classic quality-ladder models of Grossman and Helpman (1991) and Aghion and Howitt (1992), and also on the recent models of Acemoglu and Cao (2015) and Akcigit and Kerr (2015).

There is a continuum of differentiated intermediate goods on the unit interval $[0, 1]$ and firms, both entrants and incumbents, innovate by improving the quality of these intermediate goods. Final goods are produced from the intermediate goods in a competitive final good sector. We first describe the optimal aggregate consumption choice. We then describe the final good sector and the demand for each intermediate good. We then turn to the decisions of the intermediate goods firms which constitute the core of the model. Finally, we present the balanced growth equilibrium.

2.1 Consumers

The utility function of the representative consumer has the following form:

$$\mathbf{U} = \sum_{t=0}^{\infty} \beta^t [\log(C_t) - \xi L_t],$$

where C_t is consumption at time t, L_t is labor supply at time t, $\beta \in (0, 1)$ is the discount factor, and $\xi > 0$ is the parameter of the disutility of labor. Similarly to Hopenhayn and Rogerson (1993), we adopt the indivisible-labor formulation of Rogerson (1988) and L_t represents the fraction of individuals who are employed at time t.

The consumer's budget constraint is

$$A_{t+1} + C_t = (1 + r_t)A_t + w_t L_t + T_t,$$

where

$$A_t = \int_{\mathcal{N}_t} V_t^j dj$$

is the asset holding. The representative consumer owns all the firms, hence V_t^j indicates the value of a firm that produces product j at time t, and $\mathcal{N}_t$ is the set of products that are actively produced at time t.[11] In the budget constraint, r_t is the net return of the asset, w_t is the wage rate, and T_t is a lump-sum transfer (that will be used to transfer the income from the firing tax to the consumer).

The consumer's optimization results in two first-order conditions. The first is the Euler equation:

$$\frac{1}{C_t} = \beta(1 + r_{t+1})\frac{1}{C_{t+1}}, \tag{1}$$

and the second is the optimal labor-leisure choice:

$$\frac{w_t}{C_t} = \xi. \tag{2}$$

2.2 Final good firms

The final good Y_t is produced by the technology

$$Y_t = \left(\int_{\mathcal{N}_t} \mathbf{q}_{jt}{}^{\psi} y_{jt}{}^{1-\psi} dj\right)^{\frac{1}{1-\psi}}.$$

The price of Y_t is normalized to one, y_{jt} is the amount of intermediate product j used at time t and $\mathbf{q}_{jt}$ is the *realized quality* of intermediate product j.[12] The realized quality is the combination of the *potential quality* q_{jt}, which depends on the innovation decision of intermediate-good firms, and an exogenous transitory shock α_{jt}:

$$\mathbf{q}_{jt} = \alpha_{jt} q_{jt}.$$

We assume that α_{jt} is i.i.d. across time and products.[13] We also assume that the transitory shock is a product-specific shock rather than a firm-specific shock, so that the value of α_{jt} does not alter the ranking of the realized quality compared to the potential quality.[14]

[11] We do not distinguish firms and establishments in this paper. Later we use establishment-level data in our calibration. Using firm-level data yields similar results.

[12] Similar formulations are used by Luttmer (2007), Acemoglu and Cao (2015), and Akcigit and Kerr (2015), among others.

[13] The i.i.d. assumption across time is relaxed in Section 5.1.

[14] If the shock is at the firm level, it is possible that the incumbent firm i's realized quality $\alpha_{it} q_{it}$ is larger than the new firm j's realized quality $\alpha_{jt} q_{jt}$ even if $q_{jt} > q_{it}$.

Let the *average potential quality* of intermediate goods be

$$\bar{q}_t \equiv \frac{1}{N_t}\left(\int_{\mathcal{N}_t} q_{jt}dj\right),$$

where N_t is the number of actively produced products, and the *quality index* Q_t be

$$Q_t \equiv \bar{q}_t^{\frac{\psi}{1-\psi}}.$$

Note that the quality index grows at the same rate as aggregate output Y_t along the balanced-growth path.

The final good sector is perfectly competitive, and the problem for the representative final good firm is

$$\max_{y_{jt}} \quad \left(\int_{\mathcal{N}_t} \mathbf{q}_{jt}{}^{\psi} y_{jt}{}^{1-\psi} dj\right)^{\frac{1}{1-\psi}} - \int_{\mathcal{N}_t} p_{jt} y_{jt} dj.$$

The first-order condition leads to the inverse demand function for y_{jt}:

$$p_{jt} = \mathbf{q}_{jt}{}^{\psi} y_{jt}{}^{-\psi} Y_t^{\psi}. \tag{3}$$

Final-good firms are introduced for ease of exposition; as in the standard R&D-based growth models, one can easily transform this formulation into a model without final goods, assuming that the consumers and firms engaging in R&D activities combine the intermediate goods on their own.[15] In this sense, the final-good sector is a veil in the model, and we will ignore the final-good firms when we map the model to the firm dynamics data.

2.3 Intermediate good firms

The core of the model is the dynamics of the heterogeneous intermediate-good firms. Each intermediate-good firm produces one differentiated product and is the monopolist producer of that product. Intermediate-good firms enter the market, hire workers, and produce. Depending on the changes in the quality of their products, they expand or contract over time, and they may be forced to exit. Compared to standard firm dynamics models, the novelty of our model is that these dynamics are largely driven by endogenous innovations.

The intermediate firms conduct R&D activities to innovate. We consider two sources of innovations. One is the *innovation by incumbents*: an incumbent can invest in R&D

[15]See, for example, Barro and Sala-i-Martin (2004).

in order to improve the potential quality of its own product. The other is the *innovation by entrants*: an entrant can invest in R&D to innovate on a product that is either (i) not currently produced, or (ii) currently produced by another firm. If the entrant is successful at innovating, the entrant becomes the monopolist for that product and displaces the incumbent monopolist whenever the product is currently produced by another firm. The previous producer is, as a result, forced to exit.[16]

2.3.1 Production of intermediate goods

Each product j is produced by the leading-edge monopolist who produces the highest quality for that particular product. The firm's production follows a linear technology

$$y_{jt} = \ell_{jt},$$

where ℓ_{jt} is the labor input. Our main policy experiment is to impose a firing tax on intermediate-good firms. We assume that the firm has to pay the tax τw_t for each worker fired,[17] including when it exits.[18]

2.3.2 Innovation by incumbents

The incumbent producer can innovate on its own product. The probability that an incumbent innovates on its product at time t is denoted x_{Ijt}. A successful innovation increases the potential quality of the product from q_{jt} to $(1 + \lambda_I)q_{jt}$, where $\lambda_I > 0$, in the following period. The cost of innovation, $\mathbf{r}_{Ijt}$, is assumed to be

$$\mathbf{r}_{Ijt} = \theta_I Q_t \frac{q_{jt}}{\bar{q}_t} {x_{Ijt}}^{\gamma},$$

where $\gamma > 1$ and θ_I are parameters.[19]

[16] Instead of assuming that the lower-quality producer automatically exits, we can resort to a market participation game with price competition as in Akcigit and Kerr (2015).

[17] Following the literature (e.g. Hopenhayn and Rogerson (1993)), we assume that the firing costs are incurred only when the firm contracts or exits (that is, only when job destruction occurs). As is well documented (see, for example, Burgess et al. (2000)), worker flows are typically larger than job flows. The implicit assumption here is that all worker separations that are not counted as job destruction are voluntary quits that are not subject to the firing tax.

[18] An alternative specification is to assume that the firm does not need to incur firing costs when it exits. See Samaniego (2006*a*) and Moscoso Boedo and Mukoyama (2012) for discussions.

[19] The assumption that the innovation cost increases with productivity is frequently used in endogenous growth literature. See, for example, Segerstrom (1998), Howitt (2000), and Akcigit and Kerr (2015). Kortum (1997) provides empirical support for this assumption in a time-series context.

2.3.3 Innovation by entrants

A potential entrant enters after having successfully innovated on an intermediate good that is either currently produced by an incumbent or not currently produced. In order to innovate, a potential entrant has to spend a fixed cost ϕQ_t and a variable cost

$$\mathbf{r}_{Ejt} = \theta_E Q_t {x_{Ejt}}^{\gamma}$$

to innovate with probability x_{Ejt}.[20] Here, ϕ, γ and θ_E are parameters. A successful innovation increases the quality of product j from q_{jt} to $(1+\lambda_E)q_{jt}$ in the following period. The innovation step for the entrants, λ_E, is allowed to be different from the incumbents' innovation step λ_I. We assume that the entrants' innovation is not targeted: each entrant innovates on a product that is randomly selected. The entrants choose their innovation probability before learning the quality of the product they will innovate upon. An entrant innovates on an existing product with probability N_t, and on an inactive product with probability $1 - N_t$. We assume that innovating over a vacant line improves the quality of the product over a quality drawn from a given distribution $h(\hat{q})$. We denote by m_t the mass of potential entrants.

2.3.4 Exit

Firms can exit for two reasons: (i) the product line is taken over by an entrant with a better quality; (ii) the firm is hit by an exogenous, one-hoss-shay depreciation shock (exit shock). While exit is an exogenous shock from the viewpoint of the incumbent firm in both cases, the first type of exit is endogenously determined in equilibrium.[21]

The probability that an incumbent is taken over by an entrant is denoted μ_t. As we will see, this probability, which we also call the rate of creative destruction, depends on the mass of potential entrants and on the innovation intensity of each entrant. The probability of the depreciation shock, assumed to be constant across firms, is denoted by $\delta \in (0, 1)$. After this shock, the product becomes inactive until a new entrant picks up that product. From a technical viewpoint, the depreciation shock enables the economy to have a stationary distribution of (relative) firm productivity.[22]

[20] Bollard et al. (2016) provide empirical support for the assumption that entry costs increase with productivity.

[21] Note that, under the assumptions above, a firm never find it optimal to voluntarily exit. Even when the firing tax exists, the strategy of operating in a small scale today and exiting tomorrow dominates exiting immediately.

[22] See, for example, Gabaix (2009).

2.4 Timing of events and value functions

The timing of events in the model is the following. Below, we omit the firm subscript j when there is no risk of confusion.

At the beginning of period t, all innovations from last period's R&D spending realize. Incumbent firms have to exit if an entrant has innovated on their product line, including when the incumbent and the entrant innovate at the same time. Then the transitory productivity shock realizes. The firms (including new entrants) receive the depreciation shock with probability δ. Exiting firms pay the firing cost. Potential entrants and incumbents decide on their innovation rate, at the same time incumbents also choose their employment level and pay the firing costs whenever they contract. The labor market clears and production takes place. The consumer decides on consumption and saving.

We now express the firm's optimization problem as a dynamic programming problem. The expected value for the firm at the beginning of the period (after receiving the transitory shock and before receiving the depreciation shock) is

$$Z_t(q_t, \alpha_t, \ell_{t-1}) = (1-\delta)V_t^s(q_t, \alpha_t, \ell_{t-1}) + \delta V_t^o(\ell_{t-1}).$$

The first term on the right-hand side is the value from surviving and the second term is the value from exiting due to the exogenous exit shock. When exiting, the firm has to pay a firing tax on all the workers fired. The value of exiting is then

$$V_t^o(\ell_{t-1}) = -\tau w_t \ell_{t-1}.$$

The value of survival is

$$\begin{aligned} &V_t^s(q_t, \alpha_t, \ell_{t-1}) \\ &\quad = \max_{\ell_t, x_{It}} \left\{ \Pi_t(q_t, \alpha_t, \ell_{t-1}, \ell_t, x_{It}) + \frac{1}{1+r_{t+1}} \left((1-\mu_t) S_{t+1}(x_{It}, q_t, \ell_t) - \mu_t \tau w_{t+1} \ell_t\right) \right\}. \end{aligned}$$

Here, $S_{t+1}(x_{It}, q_t, \ell_t)$ is the value of not being displaced by an entrant and μ_t is the probability of being displaced by an entrant. The value of not being displaced by an entrant is

$$S_{t+1}(x_{It}, q_t, \ell_t) = (1-x_{It})E_{\alpha_{t+1}}[Z_{t+1}(q_t, \alpha_{t+1}, \ell_t)] + x_{It}E_{\alpha_{t+1}}[Z_{t+1}((1+\lambda_I)q_t, \alpha_{t+1}, \ell_t)],$$

where $E_{\alpha_{t+1}}[\cdot]$ is the expected value with respect to α_{t+1} and the period profit is

$$\Pi_t(q_t, \alpha_t, \ell_{t-1}, \ell_t, x_{It}) = ([\alpha_t q_t]^{\psi} \ell_t{}^{-\psi} Y_t{}^{\psi} - w_t)\ell_t - \theta_I Q_t \frac{q_t}{\bar{q}_t} x_{It}{}^{\gamma} - \tau w_t \max\langle 0, \ell_{t-1} - \ell_t \rangle,$$

where the inverse demand function is obtained from equation (3).

We assume free entry, that is, anyone can become a potential entrant by spending these costs. The free entry condition for potential entrants is

$$\max_{x_{E_t}} \left\{ -\theta_E Q_t x_{Ejt}{}^{\gamma} - \phi Q_t + \frac{1}{1+r_t} x_{Ejt} \bar{V}_{E,t+1} \right\} = 0, \tag{4}$$

where $\bar{V}_{E,t+1}$ is the expected value of an entrant at time $t+1$. Because the entrant decides on its innovation probability before learning its quality draw, the expected value $\bar{V}_{E,t+1}$ is constant across potential entrants and so is the innovation probability. The optimal value of the innovation probability, x^*_{Et}, is determined by

$$\frac{1}{1+r_t} \bar{V}_{E,t+1} - \gamma \theta_E Q_t x^*_{Et}{}^{\gamma-1} = 0 \tag{5}$$

Note that x^*_E is not affected by the firing tax. The response of the entry rate to changes in firing tax occurs through variation in the mass of potential entrants m_t.[23]

2.5 Balanced growth equilibrium

Because the economy exhibits perpetual growth, we first need to transform the problem into a stationary one before applying the usual dynamic programming techniques. From this section, we focus on the balanced-growth path of the economy, where w_t, C_t, Y_t, Q_t grow at a common rate g. Note that the average quality $\bar{q}_t$ grows at rate $g_q = (1+g)^{\frac{1-\psi}{\psi}} - 1$ along this path. Let us normalize all variables except q_t by dividing by Q_t. For q_t, we normalize with $\bar{q}_t$. All normalized variables are denoted with a hat ($\hat{}$): for example, $\hat{Y}_t = Y_t/Q_t$, $\hat{C}_t = C_t/Q_t$, $\hat{q}_t = q_t/\bar{q}_t$, and so on.

[23] From (4) and (5), x^*_{Et} satisfies

$$-\theta_E x^*_{Et}{}^{\gamma} - \phi + \gamma \theta_E x^*_{Et}{}^{\gamma} = 0$$

and thus x^*_{Et} is a constant number x^*_E that can easily be solved as a function of parameters. The solution is

$$x^*_E = \left(\frac{\phi}{\theta_E(\gamma - 1)} \right)^{\frac{1}{\gamma}}. \tag{6}$$

2.5.1 Normalized Bellman equations

From the consumer's Euler equation (1),

$$\beta(1 + r_{t+1}) = \frac{C_{t+1}}{C_t} = 1 + g$$

holds. Therefore $(1 + g)/(1 + r) = \beta$ holds along the stationary growth path. This can be used to rewrite the firm's value functions as the following. We use the hat notation for the stationary value functions, in order to distinguish from the previous section. The time subscripts are dropped, and we denote by ℓ the previous period employment and by ℓ' the current period employment. The value at the beginning of the period is

$$\hat{Z}(\hat{q}, \alpha, \ell) = (1 - \delta)\hat{V}^s(\hat{q}, \alpha, \ell) + \delta\hat{V}^o(\ell), \tag{7}$$

where

$$\hat{V}^o(\ell) = -\tau\hat{w}\ell.$$

The value of survival is

$$\hat{V}^s(\hat{q}, \alpha, \ell) = \max_{\ell' \geq 0, x_I} \left\{ \hat{\Pi}(\hat{q}, \alpha, \ell, \ell', x_I) + \beta \left((1 - \mu)\hat{S}\left(x_I, \frac{\hat{q}}{1 + g_q}, \ell' \right) - \mu\tau\hat{w}\ell' \right) \right\}, \tag{8}$$

where

$$\hat{S}\left(x_I, \frac{\hat{q}}{1 + g_q}, \ell' \right) = (1 - x_I)E_{\alpha'}\left[\hat{Z}\left(\frac{\hat{q}}{1 + g_q}, \alpha', \ell' \right) \right] + x_I E_{\alpha'}\left[\hat{Z}\left(\frac{(1 + \lambda_I)\hat{q}}{1 + g_q}, \alpha', \ell' \right) \right].$$

The period profit can be rewritten as

$$\hat{\Pi}(q, \alpha, \ell, \ell', x_I) = ([\alpha\hat{q}]^{\psi}\ell'^{-\psi}\hat{Y}^{\psi} - \hat{w})\ell' - \theta_I\hat{q}{x_I}^{\gamma} - \tau\hat{w}\max\langle 0, \ell - \ell' \rangle. \tag{9}$$

Note that the Bellman equation (8) can be solved for given $\hat{Y}$, $\hat{w}$, g, and μ.

For the entrants, the free entry condition can be rewritten as:

$$\max_{x_E} \left\{ -\theta_E {x_E}^{\gamma} - \phi + \beta x_E \hat{\hat{V}}_E \right\} = 0.$$

2.5.2 General equilibrium under balanced growth

Let the decision rule for x_I be $\mathcal{X}_I(\hat{q}, \alpha, \ell)$, and the decision rule for ℓ' be $\mathcal{L}'(\hat{q}, \alpha, \ell)$. Denote the stationary measure of the (normalized) individual state variables as $f(\hat{q}, \alpha, \ell)$ before the innovation and hiring decisions. Innovating over a vacant line improves the quality of the product over a quality drawn from a given distribution $h(\hat{q})$. Let Ω denote the cumulative distribution function of α and let ω denote the corresponding density function. Given these functions, we can solve for the stationary measure as the fixed point of the mapping $f \to \mathbf{T}f$, where $\mathbf{T}$ is given in Appendix A. The total mass of active product lines is

$$N \equiv \int\int\int f(\hat{q}, \alpha, \ell) d\hat{q} d\alpha d\ell.$$

From the steady-state condition, the mass of active product lines can be computed easily as[24]

$$N = \frac{\mu(1-\delta)}{\delta + \mu(1-\delta)}. \tag{10}$$

The aggregate innovation by incumbents is

$$X_I = \int\int\int \mathcal{X}_I(\hat{q}, \alpha, \ell) f(\hat{q}, \alpha, \ell) d\hat{q} d\alpha d\ell,$$

and the aggregate innovation by entrants is

$$X_E = m x_E^*.$$

The probability that an incumbent is displaced by an entrant, μ, is equal to the aggregate innovation by entrants:

$$\mu = X_E$$

Let us denote $\bar{f}$ the marginal "density" (measure) of relative productivity:

$$\bar{f}(\hat{q}) \equiv \int\int f(\hat{q}, \alpha, \ell) d\alpha d\ell.$$

Then the normalized value of entry in the stationary equilibrium can be calculated as:

$$\hat{\bar{V}}_E = \int \left[\int \hat{Z}\left(\frac{(1+\lambda_E)\hat{q}}{1+g_q}, \alpha, 0 \right) \left(\bar{f}(\hat{q}) + (1-N)h(\hat{q}) \right) d\hat{q} \right] \omega(\alpha) d\alpha.$$

In the goods market, the final goods are used for consumption and R&D, and therefore

$$\hat{Y} = \hat{C} + \hat{R},$$

holds, where $\hat{R}$ is the normalized R&D spending which includes the potential entrants' fixed cost and $\hat{C}$ is given by the labor-leisure decision (2).

[24] The equation is derived from the equality of inflows and outflows: $\delta N = \mu(1-\delta)(1-N)$.

3 Characterization of the model

The case without the firing tax can be characterized analytically. It provides a useful benchmark and gives some intuition for the determinants of innovation and growth in the model. Also, the economy without firing costs is later used to calibrate the model in the quantitative analysis. The case with the firing tax is less straightforward to characterize. We provide a partial characterization of the model with the firing tax that facilitates the numerical computation of the equilibrium.

3.1 Analytical characterization of the frictionless economy

The solution of the economy without the firing tax boils down to a system of nonlinear equations. The full characterization is in Appendix B. Here, we present several key results.

The first proposition characterizes the value function and the innovation probability of incumbents.

Proposition 1 *Given $\hat{Y}$, μ, and g_q, the value function for the incumbents is of the form*

$$\hat{Z}(\hat{q}, \alpha) = \mathcal{A}\alpha\hat{q} + \mathcal{B}\hat{q},$$

and the optimal decision for x_I is

$$x_I = \left(\frac{\beta(1-\mu)\lambda_I(\mathcal{A}+\mathcal{B})}{(1+g_q)\gamma\theta_I} \right)^{\frac{1}{\gamma-1}}$$

where

$$\mathcal{A} = (1-\delta)\psi\frac{\hat{Y}}{N}$$

and $\mathcal{B}$ solves

$$\mathcal{B} = (1-\delta)\beta(1-\mu)\left(1 + \frac{\gamma-1}{\gamma}\lambda_I x_I\right)\frac{\mathcal{A}+\mathcal{B}}{1+g_q}.$$

Proof. See Appendix B. ■

This result shows that x_I is constant across firms regardless of the values of α and $\hat{q}$. This is implies that the expected growth of a firm is independent of its size, which is consistent with *Gibrat's law*.[25] This property implies that the endogenous productivity

[25] Various studies have found that Gibrat's law holds for large firms, while many document important deviations for young and small firms (e.g. Evans (1987) and Hall (1987)). See Sutton (1997) for a survey.

process is a *stochastic multiplicative process with reset events.*[26] This process allows us to characterize the right tail of the firm productivity distribution as follows.

Proposition 2 *Suppose that the distribution of the relative productivity of vacant lines, $h(\hat{q})$, is bounded. Then the right tail of the relative firm productivity $\hat{q}$ follows a Pareto distribution with the shape parameter κ (that is, the density has a form of $F\hat{q}^{-(\kappa+1)}$) which solves*

$$1 = (1-\delta)\left[(1-\mu)x_I\gamma_i^{\kappa} + \mu\gamma_e^{\kappa} + (1-\mu-(1-\mu)x_I)\gamma_n^{\kappa}\right].$$

where $\gamma_i \equiv (1+\lambda_I)/(1+g_q)$, $\gamma_e \equiv (1+\lambda_E)/(1+g_q)$, and $\gamma_n \equiv 1/(1+g_q)$.

Proof. See Appendix B. ■

Because the firm size (in terms of employment) is log-linear in $\hat{q}$ for a given α, the right-tail of the firm size also follows the Pareto distribution with the same shape parameter κ.

Finally, we are able to characterize the growth rate of average productivity

Proposition 3 *The growth rate of average productivity is given by*

$$g_q = (1-\delta)[(1+\lambda_I x_I)(1-\mu) + (1+\lambda_E)\mu] + \delta(1+\lambda_E)\bar{q}^h - 1,$$

where $\bar{q}_h$ is the average relative productivity of inactive product lines.

Proof. See Appendix B. ■

Once the firing tax is introduced, x_I is no longer constant across firms, and therefore this formula is not valid. However, it is still useful to think of the effect of the policy on growth through these three components: the incumbents' innovation, the entrants' innovation on active products, and the entrants' innovation on inactive products.

3.2 A characterization of the economy with the firing tax

With the firing tax, the employment decision of the firm is no longer static, and therefore the characterization is not as straightforward as in the case without the firing tax. However, we can derive a partial characterization that greatly eases the computational burden of the numerical solution method. The main idea is to formulate the model in

[26] See, for example, Manrubia and Zanette (1999).

terms of the deviations from the frictionless outcome. The details of the derivation are in Appendix B.

First, define the *frictionless level of employment without temporary shock*, with $\alpha = 1$, as[27]

$$\ell^*(\hat{q}; \hat{w}, \hat{Y}) \equiv \arg\max_{\ell'} ([\hat{q}]^{\psi} \ell'^{-\psi} \hat{Y}^{\psi} - \hat{w})\ell'.$$

Let us denote by $\tilde{\ell} \equiv \ell/\ell^*(\hat{q}; \hat{w}, \hat{Y})$ the deviation of *past* employment from the *current* frictionless level and by $\tilde{\ell}' \equiv \ell'/\ell^*(\hat{q}; \hat{w}, \hat{Y})$ the deviation of *current* employment from the *current* frictionless level.

We can show that the period profit in (9) is linear in $\hat{q}$ and can be written as $\hat{q}\tilde{\Pi}(\alpha, \tilde{\ell}, \tilde{\ell}', x_I)$, where

$$\tilde{\Pi}(\alpha, \tilde{\ell}, \tilde{\ell}', x_I) \equiv \left(\left[\frac{\alpha}{\Omega(\hat{w}, \hat{Y})} \right]^{\psi} \tilde{\ell}'^{-\psi} \hat{Y}^{\psi} - \hat{w} \right) \Omega(\hat{w}, \hat{Y})\tilde{\ell}' - \theta_I {x_I}^{\gamma} - \tau \Omega(\hat{w}, \hat{Y})\hat{w} \max\langle 0, \tilde{\ell} - \tilde{\ell}' \rangle,$$

with $\Omega(\hat{w}, \hat{Y}) \equiv \ell^*(\hat{q}; \hat{w}, \hat{Y})/\hat{q}$.

All value functions are also linear in $\hat{q}$. We use the tilde notation to denote the value functions normalized by $\hat{q}$. For example $\tilde{Z}(\alpha, \tilde{\ell})$ is defined from $\hat{Z}(\hat{q}, \alpha, \ell) = \hat{q}\tilde{Z}(\alpha, \tilde{\ell})$, and equation (7) can be rewritten as

$$\tilde{Z}(\alpha, \tilde{\ell}) = (1 - \delta)\tilde{V}^s(\alpha, \tilde{\ell}) + \delta \tilde{V}^o(\tilde{\ell}),$$

where

$$\tilde{V}^o(\tilde{\ell}) = -\tau \hat{w} \Omega(\hat{w}, \hat{Y})\tilde{\ell}$$

and $\tilde{V}^s(\alpha, \tilde{\ell})$ is

$$\tilde{V}^s(\alpha, \tilde{\ell}) = \max_{\tilde{\ell}' \geq 0, x_I} \left\{ \tilde{\Pi}(\alpha, \tilde{\ell}, \tilde{\ell}', x_I) + \beta \left((1 - \mu) \frac{\tilde{S}(x_I, \tilde{\ell}')}{1 + g_q} - \mu \tau \hat{w} \Omega(\hat{w}, \hat{Y})\tilde{\ell}' \right) \right\}. \quad (11)$$

The linearity of the value functions implies that

$$\frac{\tilde{S}(x_I, \tilde{\ell}')}{1 + g_q} = (1 - x_I) E_{\alpha'} \left[\tilde{Z}\left(\alpha', (1 + g_q)\tilde{\ell}'\right) \right] \frac{1}{1 + g_q} + x_I E_{\alpha'} \left[\tilde{Z}\left(\alpha', \frac{(1 + g_q)\tilde{\ell}'}{1 + \lambda_I}\right) \right] \frac{1 + \lambda_I}{1 + g_q}$$

also holds.

The optimization problem in (11) has two choice variables, $\tilde{\ell}'$ and x_I. The first-order

[27]The frictionless level of employment is $\ell^*(\hat{q}; \hat{w}, \hat{Y}) = [(1 - \psi)/\hat{w}]^{\frac{1}{\psi}} \hat{q}\hat{Y}$.

condition for x_I is

$$\gamma\theta_I x_I^{\gamma-1} = \Gamma_I$$

and thus x_I can be computed from

$$x_I = \left(\frac{\Gamma_I}{\gamma\theta_I}\right)^{1/(\gamma-1)},$$

where $\Gamma_I \equiv \beta(1-\mu)E_{\alpha'}\left[\tilde{Z}(\alpha',(1+g_q)\tilde{\ell}'/(1+\lambda_I))(1+\lambda_I) - \tilde{Z}(\alpha',(1+g_q)\tilde{\ell}')\right]/(1+g_q)$. From here, it is easy to see that x_I is uniquely determined once we know $\tilde{\ell}'$. Let the decision rule for $\tilde{\ell}'$ in the right-hand side of (11) be $\mathcal{L}'(\alpha,\tilde{\ell})$. Then the optimal x_I can be expressed as $x_I = \mathcal{X}_I(\alpha,\tilde{\ell})$. This implies that x_I is independent of $\hat{q}$.

4 Quantitative analysis

In this section, we conduct the main experiment of the paper. We calibrate the model without firing taxes to the US economy, and analyze the effects of firing taxes on job flows, employment and output levels, and productivity growth.

4.1 Computation and calibration

The details of the computational methods are described in Appendix C. Our method involves similar steps to solving the standard general-equilibrium firm dynamics model. As in Hopenhayn and Rogerson (1993) and Lee and Mukoyama (2008), we first make a guess on relevant aggregate variables (in our case $\hat{w}$, μ, g, and $\hat{Y}$), solve the optimization problems given these variables, and then update the guess using the equilibrium conditions. This procedure is also similar to how the Bewley-Huggett-Aiyagari models of heterogeneous consumers are typically computed (see, for example, Huggett (1993) and Aiyagari (1994)). This separates our work from recent models of innovation and growth, such as Klette and Kortum (2004), Acemoglu et al. (2013), and Akcigit and Kerr (2015), as these models heavily rely on analytical characterization in a continuous-time setting. Being able to use a standardized numerical method to compute the equilibrium is particularly useful in our experiment, as the firing tax introduces a kink in the firm's objective function, which makes it difficult to obtain analytical characterizations to the maximization problem.

Following a strategy similar to Hopenhayn and Rogerson (1993), we calibrate the parameters of the model under the assumption that firing costs are equal to zero and use US data to compute our targets. In addition to the standard targets that are widely used in the macroeconomic literature, we use establishment-level labor market data to pin down the parameters that relate to the establishment dynamics.[28]

The first set of targets are relatively standard. The model period is one year. The discount factor β is set to 0.947 in line with Cooley and Prescott (1995). Similarly to Hopenhayn and Rogerson (1993), we set the value of the disutility of labor ξ so that the employment to population ratio is equal to its average value in the US. The value of ψ is set to 0.2 which implies an elasticity of substitution across goods of 5. This value is in the range of Broda and Weinstein's (2006) estimates. Our value of 0.2 implies a markup of 25%. We set the curvature of the innovation cost γ to 2. As noted by Acemoglu et al. (2013), $1/\gamma$ can be related to the elasticity of patents to R&D spending, which has been found to be between 0.3 and 0.6.[29] These estimates imply that γ is between 1.66 and 3.33.

Next, we turn to the size of the innovations by entrants and incumbents, λ_E and λ_I. As underlined by Acemoglu and Cao (2015), various studies suggest that the innovations developed by entrants are more radical than those developed by incumbents, that is $\lambda_E > \lambda_I$.[30] We set $\lambda_E = 1.5$ and $\lambda_I = 0.25$, based on the recent estimates of Bena et al. (2015). These numbers are also similar to the ones used by Acemoglu and Cao (2015). The implied innovation advantage of entrants, $(1+\lambda_E)/(1+\lambda_I)$ is equal to 2, which is also in line with estimates suggested by patent data when we interpret the number of citations of a patent as indicative of the size of the innovation embedded in the patent.[31] To set the innovation costs parameters, we assume that the cost of innovation is proportional to its size, that is $\theta_E/\theta_I = \lambda_E/\lambda_I$, and thus radical innovations are more costly than incremental innovations. We then set the level of θ_I to match the average growth rate of output per worker. When θ_I is smaller, the probability to innovate is higher, and thus the output growth rate is higher. Finally, we set ϕ to match the average job creation rate by entrants in the data. When ϕ is small, there is more entry, and therefore the job creation rate by entrants is larger. We assume that the transitory shock α is uniformly distributed, and can take three values $\{1-\varepsilon, 1, 1+\varepsilon\}$, with probability 1/3 for each value.

[28] Our model does not distinguish between firms and establishments. As 95 percent of US firms are single-establishment firms, the results would be similar if we had instead calibrated the model on firm-level labor market data.

[29] See for example Griliches (1990).

[30] One recent example is Akcigit and Kerr (2015).

[31] To approximate the innovation advantage of entrants, we look at the relative number of patent citations for entrants and incumbents. Using data on patents of Compustat firms, Balasubramanian and Lee (2008) compute the number of patent citations by firm age and find that the mean patent citation is equal to 15.7 at age 1 and equal to 8.2 at age 25, which implies a ratio of the citations at age 1 over the citations at age 25 equal to 1.9. We thank the authors for making these data available to us.

Table 1: Calibration

	Parameter	Calibrated values
Discount rate	β	0.947
Disutility of labor	ξ	1.475
Demand elasticity	ψ	0.2
Innovation step: entrants	λ_E	1.50
Innovation step: incumbents	λ_I	0.25
Innovation cost curvature	γ	2.0
Innovation cost level: entrants	θ_E	7.998
Innovation cost level: incumbents	θ_I	1.333
Entry cost	ϕ	0.1643
Exogenous exit (depreciation) rate	δ	0.001
Transitory shock	ε	0.267
Avg productivity from inactive lines	h mean	0.976
Firing tax	τ	0.0

The value of ε is set to replicate the aggregate job creation rate. The job flows are larger when ε is larger. The overall job creation rate and the job creation rate by entrants, used as targets for ϕ and ε, are computed from the Business Dynamics Statistics (BDS) published by the Census Bureau.[32] The data on the employment-to-population ratio and the growth rate of output per worker are computed from the Bureau of Labor Statistics (BLS) and the Bureau of Economic Analysis (BEA) data. All averages are computed over 1977-2012.

When an entrant innovates on an inactive product line, the entrant draws the (normalized) productivity upon which it innovates from a uniform distribution over $[0, 2\bar{q}^h]$. We set the mean $\bar{q}^h = 1$, so that the inclusion of new product lines does not alter the value of average $\hat{q}$.[33] The exogenous exit (depreciation) probability δ is set so that the tail index κ of the productivity distribution matches the value of 1.06 estimated by Axtell (2001) on the US Census data.[34] A large δ implies a larger tail index, which indicates a thinner tail.[35] The parameter values are summarized in Table 1.

Table 2 compares the baseline outcome and the targets. We also report the R&D expenditures as a share of aggregate output though we do not use it as a target in the calibration. The R&D ratio, at about 12%, is larger than what we typically see from conventional measures of R&D spending. However, because our model intends to capture

[32] The job creation rates data are publicly available at http://www.census.gov/ces/dataproducts/bds/.

[33] Note that the approximation over discrete states creates a slight deviation from the target value of 1.

[34] Axtell reports a value of 1.059. He also reports values ranging from 0.994 to 1.098 depending on the dataset used. Luttmer (2011) reports the value of 1.05 for the US firms. Ramsden and Kiss-Haypál (2000) reports the U.S. estimate of 1.25, along with estimates from other countries.

[35] See Section 3.1 for the expression of the tail index.

Table 2: Comparison between the US data and the model outcome

	Data	Model
Growth rate of output g (%)	1.48	1.48
Employment L	0.613	0.613
Tail index κ	1.06	1.06
Job creation rate (%)	17.0	17.0
Job creation rate from entry (%)	6.4	6.4
Job destruction rate (%)	15.0	17.0
Job destruction rate from exit (%)	5.3	2.8
R&D spending ratio (R/Y) (%)		11.5

Note: The growth rate and employment targets are computed using BEA and BLS data; The tail index is from Axtell's (2001) estimate; the job flows data are computed from the Census Bureau BDS dataset. The job destruction rate, job destruction rate from exit and R&D spending are not targeted in the calibration.

innovation in a broad sense, which includes productivity improvements that come from non-R&D activities such as improvements in the production process or from learning by doing, it is more appropriate the compare the model R&D spending to a broader statistic than the conventional measure of R&D. Here, the output share of R&D spending is in line with Corrado et al.'s (2009) estimate of the US intangible investments in the 1990s.

The baseline model can also be used to assess the contribution of incumbents and entrants to aggregate productivity growth.[36] Using Proposition 3, we can decompose the growth rate of output into the contribution of the incumbents' innovation and that of the entrants. The contribution of incumbents is computed as $[(1-\delta)\lambda_I x_I(1-\mu)]/g_q$ and that of entrants is $[(1-\delta)\lambda_E\mu + \delta((1+\lambda_E)\bar{q}^h - 1)]/g_q$. In the baseline calibration, we find that incumbents account for 33% of the growth rate of aggregate productivity.

4.2 Quantitative results

We now turn to our main experiment in which we evaluate the effects of firing costs. We study the effects of a firing tax $\tau = 0.3$; that is, the cost of dismissal per worker amounts to 3.6 months of wages. The choice of this level of tax is partly motivated by data from the World Bank Doing Business Dataset.[37] The Doing Business dataset reports the mandatory severance payments due by firms upon firing a worker. To ensure comparability across countries, precise assumptions are made about the firm and the

[36]See, for example, Garcia-Macia et al. (2015) who use a similar approach to decompose the growth rate of aggregate productivity growth in the US.

[37]The data are constructed from a questionnaire on employment regulations that is completed by local lawyers and public officials as well as from the reading of employment laws and regulations.

Table 3: The effects of firing costs

	Baseline $\tau = 0.0$	Experiment $\tau = 0.3$	Fixed entry $\tau = 0.3$
Growth rate of output g (%)	1.48	1.40	1.49
Average innovation probability by incumbents x_I	0.084	0.090	0.086
Innovation probability by entrants x_E	0.143	0.143	0.143
Creative destruction rate μ (%)	2.65	2.34	2.65
Employment L	100	98.7	99.7
Normalized output $\hat{Y}$	100	98.1	99.1
Normalized average productivity $\hat{Y}/L$	100	99.3	99.4
Number of active products N	0.964	0.959	0.964
Job creation rate (%)	17.0	4.9	5.4
Job creation rate from entry (%)	6.4	4.5	5.0
Job destruction rate (%)	17.0	4.9	5.4
Job destruction rate from exit (%)	2.8	2.4	2.8
R&D ratio R/Y (%)	11.5	10.7	11.7

Note: L, $\hat{Y}$, and $\hat{Y}/L$ are set at 100 in the baseline simulation.

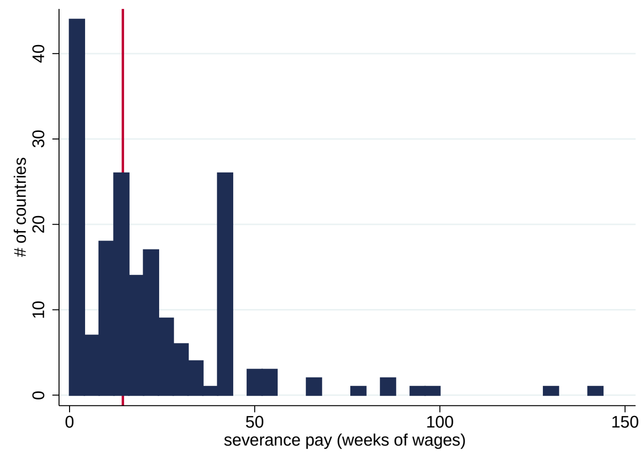
worker. The worker is assumed to be a cashier in a supermarket and the firm is assumed to have 60 workers. Figure 1 displays the distribution of severance payments across countries for this typical firm and for a typical worker with ten years of tenure. We choose to set the firing tax to 0.3 which corresponds to the median severance payments indicated by the vertical line in Figure 1.[38] Note that this is a conservative estimate of the median firing costs. Firing costs include not only severance payments but also the cost related to the length and the complexity of the dismissal procedure.[39]

The columns of Table 3 compare the baseline result with the model outcome when $\tau = 0.3$. To facilitate the comparison, the variables L, $\hat{Y}$, and $\hat{Y}/L$ are normalized to 100 in the baseline. Similarly to Hopenhayn and Rogerson (1993), employment L declines when the firing tax is imposed. The firing tax has two effects on employment. On the one hand, it reduces the firm's incentive to contract when a bad shock arrives. On the

[38] This is also close to the level of firing costs in France, estimated by Kramarz and Michaud (2010) to be 25 percent of a worker's annual wages. This a somewhat milder level of firing tax compared to what has been examined in the literature. Hopenhayn and Rogerson (1993) consider $\tau = 0.5$ and $\tau = 1.0$ (one period in their model lasts five years, therefore a firing tax of 10% in their model is equal to 50% of the annual wage). Moscoso Boedo and Mukoyama (2012) consider numbers ranging between $\tau = 0.7$ (average of high income countries) and $\tau = 1.2$ (average of low income countries). Moscoso Boedo and Mukoyama (2012) also use the Doing Business Data, but they consider a broader concept of firing tax than only severance payments.

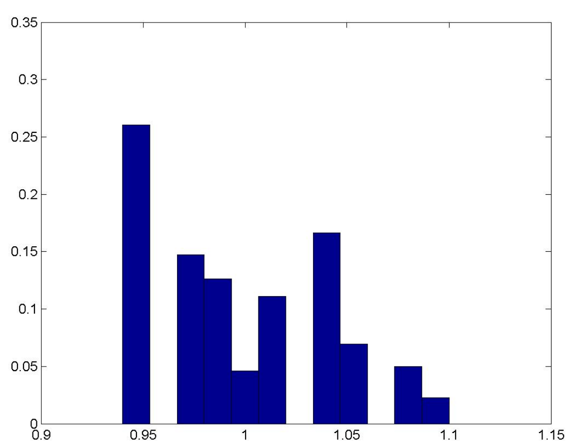
[39] Lazear (1990) argues that mandatory severance payments can potentially be undone by contractual arrangements between a firm and a worker. However, his empirical analysis shows that severance pay requirements do have real effects. Our notion of firing costs is also broader and can contain many elements other than mandatory severance payments.

Figure 1: Severance payments across the world



Notes: This figure shows the distribution of severance payments for a worker with ten years of tenure in the retail industry. The vertical line indicates the median. Source: Doing Business dataset (2015), World Bank.

Figure 2: Misallocation of labor

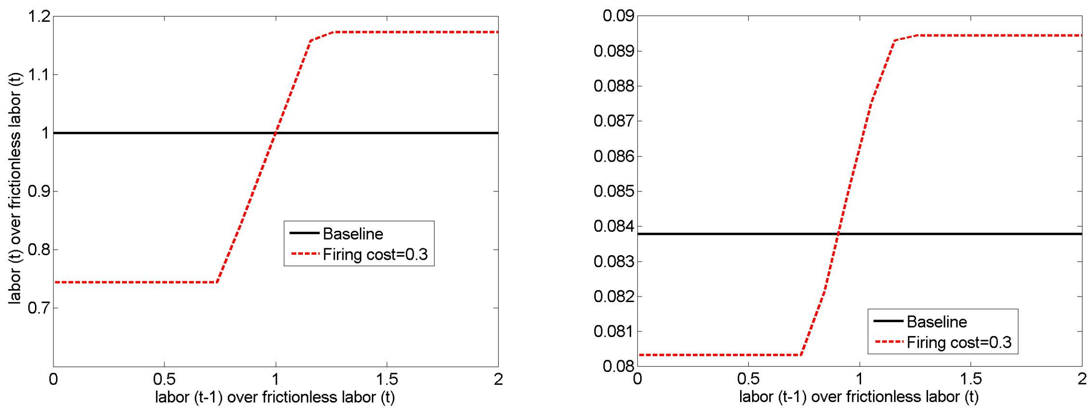


Notes: This figure shows the distribution of the marginal productivity of labor in the model for the baseline experiment where the firing tax is equal to 0.3. The marginal productivity is normalized by the wage rate $\hat{w}$. Without the firing tax, the marginal productivity of labor would be equalized across establishments and the normalized marginal productivity would be equal to 1.

Figure 3: Labor and innovation decision function, constant entry rate

(a) Labor decision

(b) Innovation probability



Notes: This figure displays the firm's labor decision in deviation from the current frictionless level $\tilde{\ell}'$ as a function of the previous labor level $\tilde{\ell}$ when μ is kept constant to its baseline value. The transitory shock is set to one.

other hand, knowing this, the firm also becomes more reluctant to hire when there is a good shock. Here, as in Hopenhayn and Rogerson (1993) and Moscoso Boedo and Mukoyama (2012), the latter effect dominates.[40]

The output level $\hat{Y}$ declines more than employment does. This is mainly because of *misallocation*: the allocation of labor across firms is not aligned with the firms' productivity when the firms face firing costs. Firms do not adjust their labor as much as they would in the frictionless economy. This can most vividly be seen by the large decline in job flows. The reduction in labor reallocation is consistent with the recent empirical evidence by Micco and Pagés (2007) and Haltiwanger et al. (2014). While the marginal product of labor is equalized across firms in the frictionless equilibrium, there is, by contrast, a notable dispersion in the marginal product of labor in the economy with a firing tax as shown in Figure 2. The marginal product of labor deviates by more than 5 percent from the equilibrium wage for about 35 percent of firms. Entry also decreases with the firing tax. As shown in the Table, this reduces the number of active intermediate products N, which further reduces the aggregate productivity level.

In addition to these *level effects* that have already been studied in the literature, our model features *growth effects*. First, firing costs reduce the entrants' incentives to innovate. The total innovation rate by entrants, represented by μ, falls by about

[40]In a recent empirical study, Autor et al. (2006) document that, during the 1970s and 1980s, many US states have adopted common-law restrictions (wrongful-discharge laws) that limits firms' ability to fire. They show that these restrictions resulted in a reduction in state employment.

0.3 percentage points.[41] The entrants' incentive to innovate is reduced because of two factors. First, the firing tax has a direct effect on expected profits as it raises the cost of operating a firm. Second, firing costs prevent firms from reaching their optimal scale and this misallocation reduces the entrants' expected profits.

By contrast, the incumbents' innovation probability *increases* by about 0.6 percentage point as a result of the firing tax. The consequences of the firing tax on the incumbents' incentive to innovate are theoretically ambiguous. On the one hand, the firing tax makes it more costly to operate the firm which reduces the profits from innovation (*direct effect*). In addition, the misallocation of labor is costly because the firm will not operate at its optimal size after innovating (*misallocation effect*). On the other hand, the firms that are larger than their optimal size, either because of a negative transitory shock or because they have been unsuccessful at innovating, now have stronger incentives to invest in R&D. A successful innovation allows these firms to avoid paying the firing tax as they no longer have to reduce their employment (*tax-escaping effect*).[42]

In addition, the incumbents' incentives to innovate further depend on the entrants' innovation (creative destruction). A lower entry rate reduces the risk for incumbents of being taken over by an entrant, which raises the return of the firm's R&D investment (*creative-destruction effect*). In effect, a lower creative destruction rate raises the planning horizon of incumbents.

To assess the importance of the creative-destruction effect, we conduct an additional experiment. There, we hold the value of μ fixed to the value in the baseline economy by not imposing the free-entry condition (5). The experiment also allows us to illustrate the ambiguous effect of the firing tax on the incumbents' innovation. Figure 3 shows the labor decision and the innovation probability of firms when entry is held constant. As is usual, the firing tax creates an inaction zone in the labor decision of the firm. We find that the shape of the innovation decision follows closely that of the labor decision. More importantly, the figure shows that the firing tax leads firms that are below their optimal size to reduce their innovation probability. As explained above, this negative effect comes from the direct tax effect and the misallocation effect. For firms that are larger than their optimal size, on the contrary, the tax-escaping effect leads to a higher innovation probability since innovating provides the added benefit of avoiding paying the firing tax.[43] Overall, the results displayed in the last column of Table 3 indicate that those

[41]Note that the equilibrium value of x_E is not affected by the tax (see equation (6)), and thus the change in μ is all due to the change in the number of potential entrants, m.

[42]Koeniger (2005) makes a related point, in the context of firm exit. In his model, one firm hires only one worker, and thus it cannot analyze the dependence on size that we emphasize.

[43]From the viewpoint of misallocation in the level, these opposite effects tend to reduce the static mis-

two effects on growth largely offset each other. When the entry rate is held constant, the incumbents' innovation increases by only 0.2 percentage point vs 0.6 percentage point in the baseline. Hence, the decline in entry accounts for two-thirds of the increase in the incumbents' innovation. This result suggests that the decline in the entry rate is the key to understanding the increase in the incumbents' innovation.

With the increase in the incumbents' innovation and the decline in the entrants' innovation, the aggregate growth rate could, in principle, increase or decrease after the introduction of the firing tax. In our baseline experiment, the negative effect on entrants dominates, and results in the reduction in the growth rate. The growth rate of output is 1.40% in the economy with the firing tax and 1.48% without the firing tax. Our results illustrate the importance of including the incumbents' innovation in the analysis. We find that firing costs can affect the innovation of entrants and incumbents in opposite directions. The overall effect depends on the details of the innovation process of entrants and incumbents. For example, ignoring the innovation by incumbents would have led us to overestimate the consequences of the firing tax on growth.

We investigate the robustness of our results to alternative calibration strategies in Appendix D. We consider calibrations with a smaller innovative advantage of entrants and with smaller innovation steps. We find that the results are qualitatively robust to these alternative calibration strategies. As in the baseline calibration, the firing tax leads to an increase in the innovation of incumbents and to a reduction in the innovation of entrants. However, it is also shown that the overall quantitative effect on aggregate growth can depend on this particular part of calibration.

5 Extensions

Our baseline model is intentionally kept simple to deliver sharp insights. While this simplicity allows us to characterize the model analytically in the absence of firing costs, it limits the ability of the model to fit the data. In this section, we relax some of the simplifying assumptions to improve the fit of the model and show that these extensions do not alter the main results of the paper. In particular, the results that the firing tax has contrasting effects on the innovations of incumbents and entrants and that it has a detrimental effect on overall growth are robust to these extensions.

In the baseline model, we assume that the exogenous productivity shock, α, is purely

allocation. Since firms that are larger than their optimal size tend to have a lower than average marginal productivity, a higher innovation probability for those firms contributes to reducing the dispersion in marginal productivity and thus this can reduce the level of misallocation.

transitory: α is assumed to be i.i.d. over time. This contrasts with the process of the endogenous productivity q, for which the upgrading is permanent. We eliminate this stark contrast in the first extension of the model and allow the process of the transitory shock α to be persistent.

In the second extension, we modify the assumptions on the entry process and on the innovation of incumbents in order to improve the predictions of the model regarding firm dynamics. A shortcoming of the baseline model is that it generates entrants that are very large. Also, existing empirical evidence suggests that Gibrat's law does not hold for small firms; small firms grow faster than large firms (see, for example, Evans (1987) and Hall (1987)). We show that these two modifications help the model better fit the microeconomic facts on firm dynamics. The resulting firm size distribution is substantially closer to the data.

5.1 Extension 1: persistent exogenous shocks

In the baseline model, the exogenous productivity shocks are assumed to be purely transitory. This simplifying assumption may affect the quantitative evaluation of the effects of the firing tax on aggregate productivity. Because the persistence of the shocks affects by how much firms adjust their employment in response to the shocks, the persistence may matter for the cost of operating a firm, and hence for the innovation decision of entrants and incumbents, as well as for the level of misallocation. In this section, we introduce persistence in the exogenous productivity shock and study the implications for the effects of the firing tax on the level and growth rate of aggregate productivity. We find that the negative effects of the firing tax are reinforced when the persistence of the exogenous productivity shock is accounted for. The persistence of the exogenous productivity shocks turns out to be more important for the level effect than for the growth effect of the firing tax.

We assume that the exogenous productivity shock α_t is persistent. As in the baseline case, α_t can take three values $\underline{\alpha}_1 = 1 - \varepsilon$, $\underline{\alpha}_2 = 1$ and $\underline{\alpha}_3 = 1 + \varepsilon$. Here, instead of assuming that α_t is randomly drawn in an i.i.d. manner, we now assume that α_t follows a Markov chain, with transition probabilities given by

$$\Pr[\alpha_{t+1} = \underline{\alpha}_j | \alpha_t = \underline{\alpha}_i] = \begin{cases} \rho & \text{if } i = j \\ (1-\rho)/2 & \text{if } i \neq j, \end{cases}$$

where ρ is the parameter that governs the persistence of the process. To identify ρ and ε, we use the variance and the autocovariance of establishment-level employment

Table 4: Persistent exogenous shock

	Baseline		Persistent α	
	$\tau = 0.0$	$\tau = 0.3$	$\tau = 0.0$	$\tau = 0.3$
Growth rate of output g (%)	1.48	1.40	1.48	1.39
Innovation probability: incumbents $\bar{x}_I$	0.084	0.090	0.084	0.089
Innovation probability: entrants x_E	0.143	0.143	0.143	0.143
Creative destruction rate μ (%)	2.65	2.34	2.66	2.33
Employment L	100	98.7	100	98.0
Normalized output $\hat{Y}$	100	98.1	100	96.8
Normalized average productivity $\hat{Y}/L$	100	99.3	100	98.8
Number of active products N	0.964	0.959	0.964	0.959
Job creation rate (%)	17.0	4.9	17.0	7.0
Job creation rate from entry (%)	6.4	4.5	6.4	4.4
Job destruction rate (%)	17.0	4.9	17.0	7.0
Job destruction rate from exit (%)	2.8	2.4	2.8	2.4
R&D ratio R/Y (%)	11.5	10.7	11.5	10.8

Note: L, $\hat{Y}$, and $\hat{Y}/L$ are set at 100 in the baseline simulation.

growth. As shown in Appendix E, the variance of employment growth is determined by the variance of changes in the endogenous productivity $\hat{q}$ and that of changes in the exogenous productivity α while the autocovariance of employment growth is a function of the variance of α and the persistence parameter. Given the parameters of the endogenous productivity process, we can then infer the size of the shock ε and the persistence parameter ρ from these two statistics. We estimate the variance and the autocovariance of establishment-level employment growth in the US using census microdata from the Longitudinal Business Database (LBD). More details on the data are given in Appendix E. We estimate the variance and autocovariance to be equal to 0.24 and -0.05, which leads us to set ρ at 0.718 and ε at 0.564. Note that this calibration implies not only more persistent shocks but also larger shocks than in the baseline. The other parameters β, ψ, λ_I, λ_E, γ, and δ are set to the same values as in the baseline case, while the parameters ϕ, ξ and θ_I are re-calibrated to match the job creation rate by entrants, the average employment rate and the average growth rate of output per worker in the US. The parameters values are reported in Table 9 and the targets are reported in Table 10, both in Appendix E.[44]

We report the results of the model with persistent exogenous shocks in Table 4. We find that when persistence is introduced, the firing tax leads to a larger decline both in the level and the growth rate of productivity.

[44]Though the overall job creation rate is not a target in this calibration, the job creation rate is equal to 17.02 which is virtually identical to the value in the baseline.

The larger decline in average productivity may be surprising as firms would adjust more of their labor in response to persistent shocks, and hence the level of misallocation should be lower when shocks are persistent. In fact, the stronger effect of the firing tax is not due to an increase in the persistence in itself. As explained above, in the new calibration, the exogenous shocks are not only persistent but also more dispersed, which raises the level of misallocation. The effects of larger shocks dominate that of higher persistence, resulting in a lower average productivity than in the baseline.

Also for the growth effect, the fact that the exogenous shocks are larger is more important than the higher persistence itself. In particular, in the new calibration the firms more frequently face situations where a large downsizing is necessary. Overall, the negative growth effect is only slightly stronger with this specification compared to the baseline case.

5.2 Extension 2: small entrants and heterogeneous growth

In this section, we maintain the assumption that α is i.i.d. as in the baseline case and extend the model in two different directions. First, we assume that entrants are more likely to innovate over lower-quality products. This is likely to be more reasonable than the assumption of random innovation, considering that innovations tend to be cumulative (see, for example, Aghion et al. (2001) and Mukoyama (2003)) and it is difficult to improve upon a very advanced product. Second, we also assume that the firms with lower (relative) quality have a lower innovation cost. Previous literature on R&D and innovation emphasizes positive spillovers across firms, and it is more likely that a lower-quality product benefits more from these spillovers. These assumptions help the model match several empirical regularities the baseline model is not able to match. First, since entrants tend to innovate over low-quality products, entrants tend to be less productive and therefore smaller compared to the baseline case. Second, since lower-quality firms, who are small, innovate more frequently, small (and young) firms tend to grow faster. This allows the model to deviate from Gibrat's law. Below, we find that the main results of the paper are robust to these modifications.

First, we modify the probability that an incumbent is taken over by an entrant so that it depends on the product's relative quality. Let $u(\hat{q})$ be the probability that an incumbent with adjusted-quality $\hat{q}$ is taken over by an entrant. We assume that $u(\hat{q})$ takes the form

$$u(\hat{q}) \equiv \frac{\omega(\hat{q})}{\bar{\omega}}\mu,$$

where $\mu = mx_E$ is the aggregate creative destruction rate and $\omega(\hat{q})$ is the weight function that determines the displacement probability of product $\hat{q}$. We assume that $\omega'(\hat{q}) \leq 0$. Given the density function of $\hat{q}$, $\bar{f}(\hat{q})/N$, the average weight $\bar{\omega}$ is defined as $\bar{\omega} \equiv \int \omega(\hat{q})\bar{f}(\hat{q})/N d\hat{q}$. Note that $u'(\hat{q}) < 0$ holds. One interpretation of this specification is that a more advanced technology is harder to be imitated. This embeds the idea of cumulative innovation (or "step-by-step innovation") of Aghion et al. (2001) and Mukoyama (2003) into our model in a parsimonious manner. The aggregate probability that an active production line is taken over is $\int u(\hat{q})\bar{f}(\hat{q})d\hat{q} = N\mu$ which is the same as the baseline model. The rest of the entrants' innovation, $(1-N)\mu$, is directed to the inactive production lines.

From the viewpoint of the entrants, once they successfully innovate, the probability that they innovate upon an active line is N and the probability that they innovate upon an inactive line is $(1-N)$. Conditional on innovating upon an active line, the density function of $\hat{q}$ that they improve upon is denoted $p(\hat{q})$, where

$$p(\hat{q}) \equiv \frac{\omega(\hat{q})}{\bar{\omega}}\frac{\bar{f}(\hat{q})}{N} = \frac{u(\hat{q})}{\mu}\frac{\bar{f}(\hat{q})}{N}.$$

Conditional on innovating upon an inactive line, the density function of $\hat{q}$ is assumed to be $h(\hat{q})$, which is the same as the baseline model. Note that when $\omega(\hat{q})$ is constant across $\hat{q}$, the specification becomes identical to the baseline model and $u(\hat{q}) = \mu$ for all $\hat{q}$ and $p(\hat{q}) = \bar{f}(\hat{q})/N$.

The second modification is that we allow the incumbents' innovation cost to depend on the firm's relative quality. We keep the same notation for the innovation cost θ_I, but instead of being a parameter, θ_I is now a function of $\hat{q}$, denoted $\theta_I(\hat{q})$.

The model structure is the same as the baseline model, except for $u(\hat{q})$, $p(\hat{q})$, and $\theta_I(\hat{q})$. The description of the rest of the model is relegated to Appendix E. The computation of this version of the model is more complex than the baseline model because the value functions are not linear in $\hat{q}$, even after the transformation on ℓ. Nevertheless, we can, once again, simplify the computation of the model by rewriting the choice of labor relative to the frictionless level.[45]

To compute the model, we must specify the weight function and the innovation cost function. We assume that the weight function takes the form

$$\omega(\hat{q}) = 1 + \chi_1 e^{-\chi_2 \hat{q}}, \tag{12}$$

where $\chi_1 \geq 0$ and $\chi_2 \geq 0$. The parameter χ_1 controls the relative displacement proba-

[45]The details of the computation method are described in Appendix E.

Table 5: Smaller entrants and the deviation from Gibrat's law

	Baseline		Extension	
	$\tau = 0.0$	$\tau = 0.3$	$\tau = 0.0$	$\tau = 0.3$
Growth rate of output g (%)	1.48	1.40	1.48	1.45
Innovation probability: incumbents $\bar{x}_I$	0.084	0.090	0.055	0.057
Innovation probability: entrants x_E	0.143	0.143	0.042	0.042
Creative destruction rate μ (%)	2.65	2.34	6.29	5.81
Employment L	100	98.7	100	98.8
Normalized output $\hat{Y}$	100	98.1	100	98.3
Normalized average productivity $\hat{Y}/L$	100	99.3	100	99.4
Number of active products N	0.964	0.959	0.984	0.983
Job creation rate (%)	17.0	4.9	17.2	5.8
Job creation rate from entry (%)	6.4	4.5	7.5	5.5
Job destruction rate (%)	17.0	4.9	17.2	5.9
Job destruction rate from exit (%)	2.8	2.4	3.2	3.1
Entry rate(%)	2.8	2.4	6.4	6.2
R&D ratio R/Y (%)	11.5	10.7	11.9	11.3

Note: L, $\hat{Y}$, and $\hat{Y}/L$ are set at 100 in the baseline simulation.

bility of high- and low-productivity firms whereas χ_2 controls the slope of the decline in the displacement probability.[46]

The innovation cost is assumed to take the form

$$\theta_I(\hat{q}) = \bar{\theta}_I(1 - (1 - \chi_3)e^{-\chi_4 \hat{q}}), \tag{13}$$

where $\bar{\theta}_I > 0$, $\chi_3 \in [0, 1]$, and $\chi_4 > 0$. The parameter χ_3 represents the relative ease of innovation for low-productivity firms.[47] The value of χ_4 influences how fast the cost increases with $\hat{q}$. The details of the calibration, including the values of the new parameters (χ_1 and χ_2 in equation (12) and χ_3 and χ_4 in equation (13)), are presented in Appendix E. As shown in Appendix E, this model better fits the data in terms of the firm size distribution.

As in Section 4, we consider an experiment of setting $\tau = 0.3$. Table 5 shows the results.[48] The baseline results are also presented for the purpose of comparison. The qualitative results are identical to those obtained with the baseline model. In particular, the contrast between the response of the incumbents' innovation and that of the entrants'

[46]Note that $\lim_{\hat{q}\to\infty} u(\hat{q})/u(0) = \lim_{\hat{q}\to\infty} \omega(\hat{q})/\omega(0) = 1/(1 + \chi_1)$.

[47]Note that $\lim_{\hat{q}\to\infty} \theta_I(\hat{q}) = \bar{\theta}_I$ and $\theta_I(0) = \chi_3\bar{\theta}_I$.

[48]It is still the case that the job creation rate by entry is larger than the entry rate in the extended model, indicating that the size of entrants is still larger than the size of incumbents. However, in comparison to the baseline case, the relative size of entrants is substantially smaller. With our functional forms, this turns out to be the lower bound of the entrants' size in the parameterizations that we can compute.

innovation is also present. The incumbents' innovation increases and the entrants' innovation decreases; the overall effect on growth is negative.

In this extended model, there is an extra incentive for incumbents to innovate. Because a firm with a larger $\hat{q}$ faces a lower probability of being replaced, an incumbent firm can avoid paying the firing tax that accompanies exit when $\hat{q}$ is large. This encourages innovation when the firing tax is imposed; the mechanism is similar to the tax-escaping effect in the previous section, but works through the incentive to avoid exit instead of expansion. Another effect is through the productivity composition of firms. Because the incumbents' innovation cost varies with $\hat{q}$, a change in the stationary composition of $\hat{q}$ has an effect on overall innovation by incumbents. The overall impact of these new additional effects on the final outcome turns out to be quantitatively small. The results of the previous section are robust to the modifications that bring the model outcome closer to the data.

6 Some evidence: the negative effects of firing costs on innovation

The quantitative results with the baseline calibration suggest that firing costs *reduce* the growth rate of the economy. However, as explained in Section 4.2, the overall effect on growth is the result of two opposing effects. Firing costs may increase the incumbents' innovation while discouraging the innovation by entrants. The overall effect could be positive or negative depending on which of these two effects dominate. To gain further insights on this question, in this section we conduct an empirical analysis of the effect of firing costs on innovation. Several studies have shown the effects of firing costs on job reallocation (Micco and Pagés, 2007; Haltiwanger et al., 2014; Davis and Haltiwanger, 2014) but only a few studies have investigated the consequences of firing costs for aggregate productivity. Using differences across the US states in the adoption of more stringent labor laws, Autor et al. (2007) find evidence suggesting that firing costs reduce total factor productivity. More closely related to our objective, Bassanini et al. (2009) investigate the effects of firing costs on total factor productivity *growth*. They find that more stringent dismissal regulations tend to reduce total factor productivity growth in industries where dismissal regulations are more likely to be binding. In this section, we complement their study by focusing on innovation spending.

6.1 Empirical specification

We analyze the effects of dismissal regulations on R&D spending following the approach used by Bassanini et al. (2009). We exploit cross-country industry level data and use a difference-in-difference strategy to asses the impact of dismissal regulations. We test whether industries that have a higher propensity to lay off workers have relatively lower R&D spending in countries where firing costs are high. Cross-industry variation is used to identify the effect of the regulation, with the underlying assumption that industries with a higher layoff propensity are more sensitive to firing costs. This strategy greatly reduces the concerns about omitted variable bias, as it allows us to control for both country and industry fixed effects. Hence, our results cannot be driven by other cross-country differences in regulations or policies as long as they do not affect industries with different layoff propensities differently.

We estimate the following equation

$$\mathsf{R\&D}_{jct} = \beta_0 + \beta_1\ \mathsf{EPL}_{ct} \times \mathsf{layoff}_j + \gamma_j + \lambda_{ct} + \varepsilon_{jct}, \tag{14}$$

where γ_j and λ_{ct} are the industry and country-time fixed effects. $\mathsf{R\&D}_{jct}$ is the R&D spending of industry j in country c and year t, computed as the share of the industry's output. We measure firing costs using an indicator of employment protection EPL_{ct}. A high value of EPL_{ct} indicates that the dismissal regulation is strict and it is thus more costly to fire workers. The indicator of the industry's propensity to lay off workers layoff_j corresponds to the industry's layoff rate in the absence of any dismissal regulations. The parameter of interest is that of the interaction between the level of employment protection and the industry's propensity to lay off workers β_1. When $\beta_1 < 0$, countries with stricter dismissal regulation have relatively lower R&D spending in industries with a higher propensity to lay off workers. Conversely, $\beta_1 > 0$ would indicate that countries with stricter dismissal regulation have relatively higher R&D spending in industries with a higher propensity to lay off workers.

We use OECD data for both the measure of R&D spending and the indictor of the strictness of dismissal regulations. The measure of R&D spending ($\mathsf{R\&D}_{jct}$) is computed as the industry's business R&D expenditures as a share of the industry's gross output at the 2-digit industry level. Business R&D expenditures are obtained from the ANBERD dataset and gross output data from STAN. For the indicator of the strictness of dismissal regulation (EPL_{ct}), we use two alternative employment protection indicators constructed by the OECD: EPL1 which measures the strictness of the regulation for individual dismissal and EPL2, which measures the strictness of the regulation for both

Table 6: Regression results, R&D ratio

	Individual dismissal EPL1			Individual and collective dismissal EPL2		
	[1]	[2]	[3]	[1]	[2]	[3]
$\mathsf{EPL}_{ct} \times \mathsf{layoff}_j$	−0.0393**	−0.0380***	−0.0335	−0.0703*	−0.0648***	−0.0416
	(0.0135)	(0.0106)	(0.0352)	(0.0281)	(0.0175)	(0.0461)
R-squared	0.352	0.588	0.598	0.309	0.588	0.598
N	5993	3201	359	3944	2328	359

Notes: The columns refer to different samples: [1] non-balanced panel [2] balanced panel [3] year=2005. The balanced panel contains data on 18 countries and 19 industries from 1995 to 2005. The non-balanced and balanced panel regressions include industry and country-time fixed effects. The 2005 regression incudes industry and country fixed effects. Robust standard errors in parentheses. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

individual and collective dismissals. Both indicators are compiled using scores between 0 and 6 with higher scores representing stricter regulation. Following Bassanini et al. (2009), we use the industry layoff rates in the US as a proxy for the propensity of each industry to layoff workers (layoff_j) since the United States is the country in our sample with the least strict dismissal regulation. We measure the US layoff rates from the 2004 "Displaced workers, Employee, Tenure and Occupational Mobility" supplement of the Current Population Survey (CPS).[49] The merged dataset contains data on 27 OECD countries and 19 industries between 1987 and 2009, with breaks and gaps in the series. A more detailed description of the data sources and the construction of the variables is provided in Appendix F.

6.2 Empirical Results

The results of the OLS estimation of equation (14) are displayed in Table 6 for the two measures of employment protection EPL1 and EPL2. The first column reports the results for the full sample. Because the data have missing observations for some industries and some countries, we also run the regression on the balanced panel (column [2]) and for a given year (column [3]) to make sure that the missing observations do not bias the results. We find evidence that stricter dismissal regulations tend to reduce R&D spending in industries where the layoff intensity is higher. Using the estimates on the full sample (column [1]), we find that a one standard deviation increase in the employment

[49] Our layoff propensity measure slightly differs from the one used in Bassanini et al. (2009), we report in Appendix F the results of the regressions when using the layoff rates reported in Bassanini et al. (2009).

protection indicator for individual dismissal (EPL1) reduces the R&D to output ratio by 0.22 percentage point more in an industry at the 90th percentile of the layoff intensity compared to an industry at the 10th percentile. A one standard deviation increase in the indicator for individual and collective dismissal (EPL2) leads to a 0.32 percentage point difference.[50] These are economically significant estimates as they represent about 15 and 20 percent of the standard deviation of the R&D ratio. In Appendix F, we evaluate the robustness of the results and report the regression results using the raw OECD R&D data and an alternative measure of the industry layoff intensity.

7 Conclusion

In this paper, we construct a general equilibrium model of firm dynamics with endogenous innovation. In contrast to standard firm dynamics models, firms decide not only on entry, production and employment, but also on investments that enhance their productivity. We use this framework to show that a policy that modifies the reallocation of inputs across firms influence not only the *level* but also the *growth* rate of aggregate productivity.

We examine a particular type of barriers: firing costs. We find that firing costs can have opposite effects on entrants' innovation and incumbents' innovation. Firing taxes reduces entrants' innovation, while it may enhance incumbents' innovation. As a result, firing costs change the composition of innovation, and to the extent that the effects on incumbents and the effects on entrants do not offset with each other, there are aggregate consequences. Our quantitative result shows that the overall effect on growth is negative, and we find some empirical support for that result.

Our model is flexible and can easily accommodate various extensions. We believe that our model will be useful for the future study of how other barriers to reallocation affect aggregate productivity growth.

[50]To compute the magnitudes we use the cross-country standard deviation of EPL1 and EPL2 in 2005, which are equal to 0.848 and 0.696, and the US layoff rates at the 10th and 90th percentiles, which are equal to 0.081 and 0.146.

References

Acemoglu, Daron and Dan Cao (2015), 'Innovation by Entrants and Incumbents', *Journal of Economic Theory* **157**, 255–294.

Acemoglu, Daron, Ufuk Akcigit, Nicholas Bloom and William R. Kerr (2013), Innovation, Reallocation and Growth, NBER Working Paper 18993.

Aghion, Philippe, Christopher Harris, Peter Howitt and John Vickers (2001), 'Competition, Imitation and Growth with Step-by-Step Innovation', *Review of Economic Studies* **68**, 467–492.

Aghion, Philippe and Peter Howitt (1992), 'A Model of Growth through Creative Destruction', *Econometrica* **60**, 323–351.

Aghion, Philippe and Peter Howitt (1994), 'Growth and Unemployment', *Review of Economic Studies* **61**, 477–494.

Aiyagari, S. Rao (1994), 'Uninsured Idiosyncratic Risk and Aggregate Saving', *Quarterly Journal of Economics* **109**, 659–684.

Akcigit, Ufuk and William R. Kerr (2015), Growth Through Heterogeneous Innovations, mimeo.

Ates, Sina T. and Felipe E. Saffie (2016), Fewer but Better: Sudden Stops, Firm Entry, and Financial Selection, mimeo.

Autor, David H., John J. Donohue and Stewart J. Schwab (2006), 'The Costs of Wrongful-Discharge Laws', *Review of Economics and Statistics* **88**, 211–231.

Autor, David H., William R. Kerr and Adriana D. Kugler (2007), 'Do Employment Protections Reduce Productivity? Evidence from U.S. States', *Economic Journal* **117**, F189–F217.

Axtell, Robert L. (2001), 'Zipf Distribution of U.S. Firm Sizes', *Science* **293**, 1818–1820.

Balasubramanian, Natarajan and Jeongsik Lee (2008), 'Firm age and innovation', *Industrial and Corporate Change* **17**(5), 1019–1047.

Barro, Robert J. and Xavier Sala-i-Martin (2004), *Economic Growth*, 2 edn, MIT Press, Cambridge.

Bassanini, Andrea, Luca Nunziata and Danielle Venn (2009), 'Job protection legislation and productivity growth in OECD countries', *Economic Policy* **24**, 349–402.

Bena, Jan, Lorenzo Garlappi and Patrick Grüning (2015), 'Heterogeneous Innovation, Firm Creation and Destruction, and Asset Prices', *Review of Asset Pricing Studies* **6**, 46–87.

Bento, Pedro and Diego Restuccia (forthcoming), 'Misallocation, Establishment Size, and Productivity', *American Economic Journal: Macroeconomics* .

Bertola, Giuseppe (1991), Flexibility, Investment, and Growth, NBER Working Papers 3864.

Bollard, Albert, Peter J. Klenow and Huiyu Li (2016), Entry Costs Rise with Development, mimeo.

Broda, C. and D. E. Weinstein (2006), 'Globalization and the gains from variety', *The Quarterly Journal of Economics* **121**(2), 541–585.

Burgess, Simon, Julia Lane and David Stevens (2000), 'Job Flows, Worker Flows, and Churning', *Journal of Labor Economics* **18**, 473–502.

Cooley, Thomas F. and Edward C. Prescott (1995), *Frontiers of Business Cycle Research*, Princeton University Press, chapter Economic Growth and Business Cycles.

Corrado, Carol, Charles Hulten and Daniel Sichel (2009), 'Intangible Capital And U.S. Economic Growth', *Review of Income and Wealth* **55**(3), 661–685.

Da-Rocha, José-María, Marina Mendes Tavares and Diego Restuccia (2016), Firing Costs, Misallocation, and Aggregate Productivity, mimeo.

Davis, Steven J. and John Haltiwanger (2014), Labor Market Fluidity and Economic Performance, NBER Working Papers 20479.

Evans, David S. (1987), 'Tests of Alternative Theories of Firm Growth', *Journal of Political Economy* **95**, 657–674.

Foster, Lucia, John C. Haltiwanger and C. J. Krizan (2001), Aggregate productivity growth. lessons from microeconomic evidence, *in* 'New Developments in Productivity Analysis', NBER, pp. 303–372.

Gabaix, Xavier (2009), 'Power Laws in Economics and Finance', *Annual Review of Economics* **1**, 255–293.

Gabler, Alain and Markus Poschke (2013), 'Experimentation by Firms, Distortions, and Aggregate Productivity', *Review of Economic Dynamics* **16**(1), 26–38.

Garcia-Macia, Daniel, Chang-Tai Hsieh and Peter J. Klenow (2015), How Destructive is Innovation?, mimeo.

Griliches, Zvi (1990), 'Patent Statistics as Economic Indicators: A Survey', *Journal of Economic Literature* **28**(4), 1661–1707.

Grossman, Gene M. and Elhanan Helpman (1991), 'Quality Ladders in the Theory of Growth', *Review of Economic Studies* **58**, 43–61.

Hall, Bronwyn H. (1987), 'The Relationship Between Firm Size and Firm Growth in the US Manufacturing Sector', *Journal of Industrial Economics* **35**, 583–606.

Haltiwanger, John, Stefano Scarpetta, and Helena Schweiger (2014), 'Cross country differences in job reallocation: The role of industry, firm size and regulations', *Labour Economics* **26**, 11–25.

Hopenhayn, Hugo A. (1992), 'Entry, Exit, and Firm Dynamics in Long Run Equilibrium', *Econometrica* **60**, 1127–1150.

Hopenhayn, Hugo and Richard Rogerson (1993), 'Job Turnover and Policy Evaluation: A General Equilibrium Analysis', *Journal of Political Economy* **101**, 915–938.

Howitt, Peter (2000), 'Endogenous growth and cross-country income differences', *American Economic Review* **90**, 829–846.

Hsieh, Chang-Tai and Peter J. Klenow (2009), 'Misallocation and manufacturing tfp in china and india', *Quarterly Jounral of Economics* **124**, 1403–1448.

Huggett, Mark (1993), 'The Risk-Free Rate in Heterogeneous-Agent Incomplete-Insurance Economies', *Journal of Economic Dynamics and Control* **17**, 953–969.

Klette, Tor Jakob and Samuel Kortum (2004), 'Innovating Firms and Aggregate Innovation', *Journal of Political Economy* **112**, 986–1018.

Koeniger, Winfried (2005), 'Dismissal Costs and Innovation', *Economics Letters* **88**, 79–84.

Kortum, Samuel (1997), 'Research, Patenting, and Technological Change', *Econometrica* **65**, 1389–1420.

Kramarz, Francis and Marie-Laure Michaud (2010), 'The shape of hiring and separation costs in France', *Labour Economics* **17**(1), 27–37.

Lazear, Edward P. (1990), 'Job Security Provisions and Employment', *Quarterly Journal of Economics* **105**, 699–726.

Lee, Yoonsoo and Toshihiko Mukoyama (2008), Entry, Exit and Plant-level Dynamics over the Business Cycle, Federal Reserve Bank of Cleveland Working Paper 07-18R.

Luttmer, Erzo G. J. (2007), 'Selection, Growth, and Size Distribution of Firms', *Quarterly Journal of Economics* **122**, 1103–1144.

Luttmer, Erzo G. J. (2011), 'On the Mechanics of Firm Growth', *Review of Economic Studies* **78**, 1042–1068.

Manrubia, Susanna C. and Damián H. Zanette (1999), 'Stochastic Multiplicative Processes with Reset Events', *Physica Review E* **59**, 4945–4948.

Micco, Alejandro and Carmen Pagés (2007), The Economic Effects of Employment Protection: Evidence from International Industry-level Data, mimeo.

Moscoso Boedo, Hernan and Toshihiko Mukoyama (2012), 'Evaluating the Effects of Entry Regulations and Firing Costs on International Income Differences', *Journal of Economic Growth* **17**, 143–170.

Mukoyama, Toshihiko (2003), 'Innovation, Imitation, and Growth with Cumulative Technology', *Journal of Monetary Economics* **50**, 361–380.

Osotimehin, Sophie (2016), Aggregate Productivity and the Allocation of Resources over the Business Cycle, mimeo.

Peters, Michael (2016), Heterogeneous markups, growth and endogenous misallocation.

Poschke, Markus (2009), 'Employment Protection, Firm Selection, and Growth', *Journal of Monetary Economics* **56**, 1074–1085.

Ramsden, J. J. and Gy. Kiss-Haypál (2000), 'Company Size Distribution in Different Sizes', *Physica A* **277**, 220–227.

Restuccia, Diego and Richard Rogerson (2008), 'Policy distortions and aggregate productivity with heterogeneous plants', *Review of Economic Dynamics* **11**, 707–720.

Rogerson, Richard (1988), 'Indivisible labor, lotteries and equilibrium', *Journal of Monetary Economics* **21**.

Saint-Paul, Gilles (2002), 'Employment Protection, International Specialization, and Innovation', *European Economic Review* **46**, 375–395.

Samaniego, Roberto (2006*a*), 'Do Firing Costs Affect the Incidence of Firm Bankruptcy?', *Macroeconomic Dynamics* **10**, 467–501.

Samaniego, Roberto (2006*b*), 'Employment Protection and High-tech Aversion', *Review of Economic Dynamics* **9**, 224–241.

Samaniego, Roberto M. (2008), 'Can technical change exacerbate the effects of labor market sclerosis', *Journal of Economic Dynamics and Control* **32**(2), 497–528.

Segerstrom, Paul S. (1998), 'Endogenous Growth without Scale Effects', *American Economic Review* **88**, 1290–1310.

Segerstrom, Paul S. and James Zolnierek (1999), 'The R&D Incentives of Industry Leaders', *International Economic Review* **40**, 745–766.

Sutton, John (1997), 'Gibrat's Legacy', *Journal of Economic Literature* **35**, 40–59.

U.S. Census Bureau (2011), Synthetic LBD Beta version 2.0, [computer file], U.S. Census Bureau and Cornell University, Synthetic Data Server [distributor], Washington,DC and Ithaca, NY, USA.

Appendix (not for publication)

A Stationary distribution

The stationary measure is the fixed point of the mapping $f \to \mathbf{T}f$, where $\mathbf{T}f$ gives the probability for the next period state given that the current state is drawn according to the probability measure f. The mass of firms in the set $[0, q'] \times [0, \alpha'] \times [0, \ell']$ next period is given by

$$\int_0^{\alpha'} \int_0^{\ell'} \int_0^{\hat{q}'} \mathbf{T}f(\hat{q}, \alpha, \ell) d\hat{q} d\alpha d\ell = (1-\delta)[(1-\mu)M_s(\hat{q}', \alpha', \ell') + M_e(\hat{q}', \alpha', \ell')].$$

The first term M_s is the mass of non-displaced firms.

$$\begin{aligned} M_s(\hat{q}', \alpha', \ell') = \; & \int_0^{\alpha'} \int_\alpha \int_{\hat{q}/(1+g_q) \leq \hat{q}'} \int_{\mathcal{L}'(\hat{q},\alpha,\ell) \leq \ell'} g_\alpha(\alpha')(1 - \mathcal{X}_I(\hat{q}, \alpha, \ell)) f(\hat{q}, \alpha, \ell) d\hat{q} d\ell d\alpha d\alpha' \\ & + \int_0^{\alpha'} \int_\alpha \int_{(1+\lambda_I)\hat{q}/(1+g_q)} \int_{\mathcal{L}'(\hat{q},\alpha,\ell) \leq \ell'} g_\alpha(\alpha') \mathcal{X}_I(\hat{q}, \alpha, \ell) f(\hat{q}, \alpha, \ell) d\hat{q} d\ell d\alpha d\alpha'. \end{aligned}$$

The second term M_e is the mass of entering firms, which includes firms entering on inactive products and firms entering on existing products:

$$\begin{aligned} M_e(\hat{q}', \alpha', \ell') = \; & \mu(1-N) \int_0^{\alpha'} \int_\alpha \int_{(1+\lambda_E)\hat{q}/(1+g_q) \leq \hat{q}'} h(\hat{q}) \bar{g}(\alpha') d\hat{q} d\alpha' \\ & + \mu \int_0^{\alpha'} \int_\alpha \int_{(1+\lambda_E)\hat{q}/(1+g_q) \leq \hat{q}'} \int g_\alpha(\alpha') f(\hat{q}, \alpha, \ell) d\hat{q} d\ell d\alpha d\alpha', \end{aligned}$$

where $\bar{g}(\alpha')$ is the invariant distribution of the transitory shock.

The expression of the stationary distribution is simpler when the model is rewritten in deviation to the frictionless values (see Section 3.2) and when the transitory shock α is i.i.d. as assumed in the baseline calibration. In that case, the stationary distribution can then be rewritten as a function of the deviation of labor from its frictionless value $\tilde{\ell}$ instead of ℓ and the next period transitory shock draw becomes independent of next period productivity and labor states.

With these two modifications, M_s becomes

$$M_s(\hat{q}',\alpha',\tilde{\ell}') = \; G(\alpha')\left[\int_\alpha \int_{\hat{q}/(1+g_q)\le \hat{q}'} \int_{\mathcal{L}'(\alpha,\ell)\le \tilde{\ell}'} (1-\mathcal{X}_I(\alpha,\tilde{\ell}))f(\hat{q},\alpha,\tilde{\ell})d\hat{q}d\alpha d\tilde{\ell} \right.$$
$$\left. + \int_\alpha \int_{(1+\lambda_I)\hat{q}/(1+g_q)} \int_{\mathcal{L}'(\alpha,\tilde{\ell})\le \tilde{\ell}'} \mathcal{X}_I(\alpha,\tilde{\ell})f(\hat{q},\alpha,\tilde{\ell})d\hat{q}d\alpha d\tilde{\ell}\right].$$

The mass of entrants M_e can be rewritten as

$$M_e(\hat{q}',\alpha',\tilde{\ell}') = \; G(\alpha')\left[\mu(1-N)\int_\alpha \int_{(1+\lambda_E)\hat{q}/(1+g_q)\le \hat{q}'} h(\hat{q})d\hat{q} \right.$$
$$\left. + \mu \int_\alpha \int_{(1+\lambda_E)\hat{q}/(1+g_q)\le \hat{q}'} \int\int f(\hat{q},\alpha,\tilde{\ell})d\hat{q}d\tilde{\ell}d\alpha\right].$$

B Analytical characterizations

This section characterizes the model without the firing tax and boils it down to a system of nonlinear equations. The derivations also serve as proofs for the Propositions.

B.1 Model solution

Note first that for a given μ, the number of actively produced product, N, is calculated by (10). Recall that μ is an endogenous variable and is determined by the entrants' innovation:

$$\mu = m{x_E}^*.$$

As we have seen, ${x_E}^*$ is given by

$${x_E}^* = \left(\frac{\phi}{\theta_E(\gamma-1)}\right)^{\frac{1}{\gamma}},$$

and thus μ (and also N) is a function of m. In particular, note that N is an increasing function of m.

Because there are no firing taxes, the previous period employment, ℓ, is not a state variable anymore. The measure of individual states can be written as $f(\hat{q},\alpha)$, and because $\hat{q}$ and α are independent, we can write $f(\hat{q},\alpha) = \hat{z}(\hat{q})g(\alpha)$. In particular, note that $\int \hat{q}\hat{z}(\hat{q})d\hat{q} = N$, because $\hat{q}$ is the value of q_t normalized by its average. We also assume that $g(\alpha)$ is such that $\int \alpha g(\alpha)d\alpha = 1$.

Without firing costs, labor can be adjusted freely. Thus the intermediate-good firm's decision for ℓ' is static:

$$\max_{\ell'} \quad \hat{\pi} \equiv ([\alpha \hat{q}]^{\psi} \ell'^{-\psi} \hat{Y}^{\psi} - \hat{w})\ell'. \tag{15}$$

From the first-order condition,

$$\ell' = \left(\frac{1-\psi}{\hat{w}}\right)^{\frac{1}{\psi}} \alpha \hat{q} \hat{Y} \tag{16}$$

holds. Because $y = \ell'$, we can plug this into the definition of $\hat{Y}$:

$$\hat{Y} = \left(\int \int [\alpha \hat{q}]^{\psi} y^{1-\psi} \hat{z}(\hat{q}) \omega(\alpha) d\hat{q} d\alpha\right)^{\frac{1}{1-\psi}}.$$

This yields

$$\hat{Y} = \hat{Y} \left(\frac{1-\psi}{\hat{w}}\right)^{\frac{1}{\psi}} N^{\frac{1}{1-\psi}}$$

and therefore

$$\hat{w} = (1-\psi) N^{\frac{\psi}{1-\psi}}. \tag{17}$$

Recall that N is a function of the endogenous variable m. Thus $\hat{w}$ is also a function of m.

Combining the equations (16) and (17), we get

$$\ell' = \alpha \hat{q} \hat{Y} N^{-\frac{1}{1-\psi}}. \tag{18}$$

Integrating this across all active firms yields

$$L = N^{-\frac{\psi}{1-\psi}} \hat{Y}.$$

One way of looking at this equation is that $\hat{Y}$ can be pinned down once we know L and N (and thus L and m). Plugging (17) and (18) into (15) yields

$$\hat{\pi} = \psi \alpha \hat{q} \frac{\hat{Y}}{N}.$$

Now, let us characterize the innovation decision of a intermediate-good firm. Recall that the value functions are

$$\hat{Z}(\hat{q}, \alpha) = (1-\delta) \hat{V}^{s}(\hat{q}, \alpha),$$

where

$$\hat{V}^s(\hat{q},\alpha) = \max_{x_I} \quad \psi\alpha\hat{q}\frac{\hat{Y}}{N} - \theta_I\hat{q}{x_I}^\gamma + \beta(1-\mu)\hat{S}(x_I,\hat{q}/(1+g_q)) \tag{19}$$

and

$$\hat{S}(x_I,\hat{q}/(1+g_q)) = (1-x_I)\int \hat{Z}(\hat{q}/(1+g_q),\alpha')\omega(\alpha')d\alpha' + x_I\int \hat{Z}((1+\lambda_I)\hat{q}/(1+g_q),\alpha')\omega(\alpha')d\alpha'.$$

We start from making a guess that $\hat{Z}(\hat{q},\alpha)$ takes the form

$$\hat{Z}(\hat{q},\alpha) = \mathcal{A}\alpha\hat{q} + \mathcal{B}\hat{q},$$

where $\mathcal{A}$ and $\mathcal{B}$ are constants. With this guess, the first-order condition in (19) for x_I is

$$\gamma\theta_I\hat{q}{x_I}^{\gamma-1} = \frac{\beta(1-\mu)\lambda_I(\mathcal{A}+\mathcal{B})\hat{q}}{1+g_q}.$$

Thus

$$x_I = \left(\frac{\beta(1-\mu)\lambda_I(\mathcal{A}+\mathcal{B})}{(1+g_q)\gamma\theta_I}\right)^{\frac{1}{\gamma-1}} \tag{20}$$

and x_I is constant across $\hat{q}$ and α. Substituting for x_I, the value function can be written

$$\hat{Z}(\hat{q},\alpha) = (1-\delta)\left(\psi\alpha\hat{q}\frac{\hat{Y}}{N} - \theta_I\hat{q}{x_I}^\gamma + \beta(1-\mu)\frac{1+x_I\lambda_I}{1+g_q}(\mathcal{A}+\mathcal{B})\hat{q}\right).$$

Thus, the guess is verified with

$$\mathcal{A} = (1-\delta)\psi\frac{\hat{Y}}{N}$$

and $\mathcal{B}$ solves

$$\mathcal{B} = (1-\delta)\left(-\theta_I{x_I}^\gamma + \beta(1-\mu)\frac{1+x_I\lambda_I}{1+g_q}(\mathcal{A}+\mathcal{B})\right) = (1-\delta)\beta(1-\mu)\left(1+\frac{\gamma-1}{\gamma}\lambda_I x_I\right)\frac{\mathcal{A}+\mathcal{B}}{1+g_q},$$

where x_I is given by (20). Therefore, we found that x_I (and the coefficients of the function $\hat{Z}(\hat{q},\alpha)$) is a function of the endogenous aggregate variables μ, g_q, $\hat{Y}$, and N. We have already seen that we can pin down μ and N if we know m, and $\hat{Y}$ can be pinned down if we know m and L.

We now turn to the growth rate of productivity g_q. As we have seen above, the transitory shock α does not affect the innovation decision and can therefore be ignored when calculating the transition function of q_t. Consider the measure of productivity (without the normalization) q_t for active products, $z(q_t)$. A fraction $(1-\mu)x_I(1-\delta)$ of active lines are products that have been innovated upon by incumbents and the fraction $(1-\mu-(1-\mu)x_I)(1-\delta)$ is owned by the incumbents but the innovation was unsuccessful. The fraction $\mu(1-\delta)$ of active products is innovated upon by entrants. The fraction $\mu(1-\delta)$ of inactive products is innovated upon by entrants. The productivity distribution of inactive product lines is $h(q_t/\bar{q}_t)$ rather than $z(q_t)/N$. Thus g_q can be calculated from

$$1+g_q=(1-\delta)\left[(1+\lambda_I x_I)(1-\mu)+(1+\lambda_E)\mu+(1+\lambda_E)\mu\frac{1-N}{N}\frac{\bar{q}^h}{\bar{q}^z}\right],$$

where $\bar{q}^h$ and $\bar{q}^z$ are averages of q_t with respect to the distributions h and z. Thus $\bar{q}^h/\bar{q}^z = \int q_t h(q_t/\bar{q}_t)dq_t/\int q_t[z(q_t)/N]dq_t = \int \hat{q}h(\hat{q})d\hat{q}/\int \hat{q}[\hat{z}(\hat{q})/N]d\hat{q}$. The first term is the productivity increase of the surviving incumbents, the second term is the entry into active products, and the last is the entry into inactive products. Using the expression for N in (10) and the fact that $\bar{q}^z=1$,

$$g_q=(1-\delta)[(1+\lambda_I x_I)(1-\mu)+(1+\lambda_E)\mu]+\delta(1+\lambda_E)\bar{q}^h-1.$$

Thus, g_q can be written as a function of μ and x_I, and therefore m and L.

Hence, we can determine all endogenous variables in the economy once we pin down m and L. The values of m and L can be pinned down by two additional conditions: the labor-market equilibrium condition and the free-entry condition. To see this, let us first be explicit about each variable's (and each coefficient's) dependence on m and L: $\hat{w}(m)$, $N(m)$, $\hat{Y}(m,L)$, $x_I(m,L)$, $g_q(m,L)$, $\mathcal{A}(m,L)$, and $\mathcal{B}(m,L)$. Also note that the total R&D, $\hat{R}$, can be written as

$$\hat{R}=\int \theta_I\hat{q}x_I(m,L)^\gamma\hat{z}(\hat{q})d\hat{q}+m(\phi+\theta_E {x_E}^\gamma)=\theta_I N(m)x_I(m,L)^\gamma+m(\phi+\theta_E {x_E}^\gamma)$$

and therefore we can write $\hat{R}(m,L)$.

The labor-market equilibrium condition is

$$\frac{\hat{w}(m)}{\hat{Y}(m,L)-\hat{R}(m,L)}=\xi$$

and the free-entry condition is

$$\frac{\gamma\theta_E {x_E}^{\gamma-1}}{\beta}=\hat{\hat{V}}_E,$$

where

$$\begin{aligned}
\hat{\hat{V}}_E &= \int \left[\int \hat{Z}((1+\lambda_E)\hat{q}/(1+g_q), \alpha)(\hat{z}(\hat{q}) + (1-N)h(\hat{q}))d\hat{q} \right] \omega(\alpha) d\alpha \\
&= \int \frac{\mathcal{A}(m,L) + \mathcal{B}(m,L)}{1+g_q(m,L)} (1+\lambda_E)\hat{q}(\hat{z}(\hat{q}) + (1-N)h(\hat{q}))d\hat{q} \\
&= \frac{\mathcal{A}(m,L) + \mathcal{B}(m,L)}{1+g_q(m,L)} (1+\lambda_E)[N(m) + (1-N(m))\bar{q}^h].
\end{aligned}$$

B.2 Productivity distribution

The invariant distribution $\hat{z}(\hat{q})$ can be easily computed. The next-period mass at relative quality $\hat{q}$ is the sum of four components: (i) the incumbents' innovation: $(1-\delta)(1-\mu)x_I\hat{z}((1+g_q)\hat{q}/(1+\lambda_I))d\hat{q}$, (ii) the entrants' innovation: $(1-\delta)\mu\hat{z}((1+g_q)\hat{q}/(1+\lambda_E))d\hat{q}$, (iii) the downgrade from products that were not innovated upon: $((1-\delta)(1-\mu-(1-\mu)x_I)\hat{z}((1+g_q)\hat{q})d\hat{q}$, and (iv) the entry from inactive products, $(1-\delta)\mu(1-N)h(\hat{q}/(1+\lambda_E))dq$. The sum of these four components has to be equal to $\hat{z}(\hat{q})d\hat{q}$ along the stationary growth path.

We can characterize the right tail of the distribution analytically, when the distribution $h(\hat{q})$ is bounded. Let the density function of the stationary distribution be $s(\hat{q}) \equiv \hat{z}(\hat{q})/N$. Because $h(\hat{q})$ is bounded, there is no direct inflow from the inactive product lines at the right tail.

Consider the point $\hat{q}$ and the interval Δ around that point. The outflow from that interval is $s(\hat{q})\Delta$, as all the firms will either move up, move down, or exit.

The inflow comes from two sources. The first source is the mass of firms who innovated. Innovation is either done by incumbents or entrants. Let $\gamma_i \equiv (1+\lambda_I)/(1+g_q) > 1$ be the (adjusted) improvement of $\hat{q}$ after innovation by an incumbent. The probability of innovation by an incumbent is $(1-\delta)(1-\mu)x_I$ and the corresponding mass of this inflow is $(1-\delta)(1-\mu)x_I s(\hat{q}/\gamma_i)\Delta/\gamma_i$. Similarly, letting $\gamma_e \equiv (1+\lambda_E)/(1+g_q) > 1$ be the improvement of $\hat{q}$ after innovation by an entrant, the mass of the inflow due to the entrants' innovation is $(1-\delta)\mu s(\hat{q}/\gamma_e)\Delta/\gamma_e$. The second source of inflow is the surviving firms that did not innovate. With probability $(1-\delta)(1-\mu)(1-x_I)$, incumbents firms are not successful at innovating. Let $\gamma_n \equiv 1/(1+g_q) < 1$ be the (adjusted) quality ratio when there is no innovation. The corresponding mass of this inflow is $(1-\delta)(1-\mu)(1-x_I)s(\hat{q}/\gamma_n)\Delta/\gamma_n$.

In the stationary distribution, the inflows are equal to the outflows, and therefore

$$s(\hat{q})\Delta = (1-\delta)\left[(1-\mu)x_I s\left(\frac{\hat{q}}{\gamma_i}\right)\frac{\Delta}{\gamma_i} + \mu s\left(\frac{\hat{q}}{\gamma_e}\right)\frac{\Delta}{\gamma_e} + (1-\mu-(1-\mu)x_I)s\left(\frac{\hat{q}}{\gamma_n}\right)\frac{\Delta}{\gamma_n}\right],$$

or

$$s(\hat{q}) = (1-\delta)\left[(1-\mu)x_I s\left(\frac{\hat{q}}{\gamma_i}\right)\frac{1}{\gamma_i} + \mu s\left(\frac{\hat{q}}{\gamma_e}\right)\frac{1}{\gamma_e} + (1-\mu-(1-\mu)x_I)s\left(\frac{\hat{q}}{\gamma_n}\right)\frac{1}{\gamma_n}\right],$$

Guess that the right-tail of the density function is Pareto and has the form $s(x) = Fx^{-(\kappa+1)}$. The parameter $\kappa >$ is the shape parameter and the expected value of x exists only if $\kappa > 1$. Plugging this guess into the expression above yields

$$\begin{aligned} F\hat{q}^{-(\kappa+1)} = & \\ & (1-\delta)\left[(1-\mu)x_I F\left(\frac{\hat{q}}{\gamma_i}\right)^{-(\kappa+1)}\frac{1}{\gamma_i} + \mu F\left(\frac{\hat{q}}{\gamma_e}\right)^{-(\kappa+1)}\frac{1}{\gamma_e}\right. \\ & \left. + (1-\mu-(1-\mu)x_I)F\left(\frac{\hat{q}}{\gamma_n}\right)^{-(\kappa+1)}\frac{1}{\gamma_n}\right], \end{aligned}$$

or

$$1 = (1-\delta)\left[(1-\mu)x_I\gamma_i^{\kappa} + \mu\gamma_e^{\kappa} + (1-\mu-(1-\mu)x_I)\gamma_n^{\kappa}\right].$$

The parameter κ is the solution of this equation.

B.3 Growth rate

The growth rate of aggregate productivity is given by

$$g_q = (1-\delta)[(1+\lambda_I x_I)(1-\mu) + (1+\lambda_E)\mu] + \delta(1+\lambda_E)\bar{q}^h - 1,$$

where $\bar{q}_h$ is the average relative productivity of inactive product lines. This can be shown by a simple accounting relation. Let the measure of q_t (without normalization) for active products be $z(q_t)$.[51] Innovation by incumbents occurs on a fraction $(1-\mu)x_I(1-\delta)$ of active product lines, no innovation occurs on a fraction $(1-\mu-(1-\mu)x_I)(1-\delta)$ of active lines. There is innovation by entrants on a fraction $\mu(1-\delta)$ of active products. Among the inactive products, the fraction $\mu(1-\delta)$ becomes active from the innovation by entrants, but it is an upgrade from the distribution $h(q_t/\bar{q}_t)$ rather than $z(q_t)/N$. Thus g_q can be calculated from

$$1 + g_q = (1-\delta)\left[(1+\lambda_I x_I)(1-\mu) + (1+\lambda_E)\mu + (1+\lambda_E)\mu\frac{1-N}{N}\frac{\bar{q}^h}{\bar{q}^z}\right].$$

[51] In relation to the general model, $z(q_t)$ corresponds to $\bar{f}(q_t/\bar{q}_t)$ in terms of $\bar{f}$ in Section 2.5.2. The normalized version $\hat{z}(\hat{q})$ exactly corresponds to $\bar{f}(\hat{q})$.

Here, $\bar{q}^h$ and $\bar{q}^z$ are averages of q_t with respect to the distributions h and z. Thus $\bar{q}^h/\bar{q}^z = \int q_t h(q_t/\bar{q}_t)dq_t / \int q_t[z(q_t)/N]dq_t = \int \hat{q}h(\hat{q})d\hat{q} / \int \hat{q}[\hat{z}(\hat{q})/N]d\hat{q}$. Combining this with the expression for N in (10) and the fact that $\bar{q}^z = 1$ yields the above result.

B.4 Details of Section 3.2

Under the notations of Section 3.2, the period profit (9) can be rewritten as

$$\hat{\Pi}(\hat{q}, \alpha, \ell, \ell', x_I) = \\ \left(\left[\frac{\alpha}{\Omega(\hat{w}, \hat{Y})} \right]^{\psi} \tilde{\ell}'^{-\psi} \hat{Y}^{\psi} - \hat{w} \right) \hat{q}\Omega(\hat{w}, \hat{Y})\tilde{\ell}' - \theta_I \hat{q} x_I{}^{\gamma} - \tau \hat{w} \max\langle 0, \hat{q}\Omega(\hat{w}, \hat{Y})\tilde{\ell} - \hat{q}\Omega(\hat{w}, \hat{Y})\tilde{\ell}' \rangle.$$

Thus this is linear in $\hat{q}$, and can be rewritten as $\hat{q}\tilde{\Pi}(\alpha, \tilde{\ell}, \tilde{\ell}', x_I)$, where

$$\tilde{\Pi}(\alpha, \tilde{\ell}, \tilde{\ell}', x_I) \equiv \left(\left[\frac{\alpha}{\Omega(\hat{w}, \hat{Y})} \right]^{\psi} \tilde{\ell}'^{-\psi} \hat{Y}^{\psi} - \hat{w} \right) \Omega(\hat{w}, \hat{Y})\tilde{\ell}' - \theta_I x_I{}^{\gamma} - \tau \Omega(\hat{w}, \hat{Y}) \hat{w} \max\langle 0, \tilde{\ell} - \tilde{\ell}' \rangle.$$

Because the period return function is linear in $\hat{q}$, it is straightforward to show that all value functions are linear in $\hat{q}$. Defining $\tilde{Z}(\alpha, \tilde{\ell})$ from $\hat{Z}(\hat{q}, \alpha, \ell) = \hat{q}\tilde{Z}(\alpha, \tilde{\ell})$, (7) can be rewritten as

$$\tilde{Z}(\alpha, \tilde{\ell}) = (1 - \delta)\tilde{V}^s(\alpha, \tilde{\ell}) + \delta \tilde{V}^o(\tilde{\ell}),$$

where $\tilde{V}^o(\tilde{\ell})$ is from $\hat{V}^o(\ell) = \hat{q}\tilde{V}^o(\tilde{\ell})$ and thus

$$\tilde{V}^o(\tilde{\ell}) = -\tau \hat{w} \Omega(\hat{w}, \hat{Y})\tilde{\ell}$$

and $\tilde{V}^s(\alpha, \tilde{\ell})$ is from $\hat{V}^s(\hat{q}, \alpha, \ell) = \hat{q}\tilde{V}^s(\alpha, \tilde{\ell})$ with

$$\tilde{V}^s(\alpha, \tilde{\ell}) = \max_{\tilde{\ell}' \geq 0, x_I} \left\{ \tilde{\Pi}(\alpha, \tilde{\ell}, \tilde{\ell}', x_I) + \beta \left((1 - \mu) \frac{\tilde{S}(x_I, \tilde{\ell}')}{1 + g_q} - \mu \tau \hat{w} \Omega(\hat{w}, \hat{Y}) \tilde{\ell}' \right) \right\}$$

Here, the expression $\tilde{S}(x_I, \tilde{\ell}')/(1+g_q)$ comes from $\hat{S}(x_I, \hat{q}/(1+g_q), \ell') = \hat{q}\tilde{S}(x_I, \tilde{\ell}')/(1+g_q)$. The linearity of the value functions implies that

$$\frac{\tilde{S}(x_I, \tilde{\ell}')}{1 + g_q} = (1 - x_I) E_{\alpha'} \left[\tilde{Z}\left(\alpha', (1 + g_q)\tilde{\ell}' \right) \right] \frac{1}{1 + g_q} + x_I E_{\alpha'} \left[\tilde{Z}\left(\alpha', \frac{(1 + g_q)\tilde{\ell}'}{1 + \lambda_I} \right) \right] \frac{1 + \lambda_I}{1 + g_q}$$

also holds. Here we used that

$$\hat{Z}(\hat{q}', \alpha', \ell') = \hat{q}'\tilde{Z}\left(\alpha', \frac{\ell'}{\ell^*(\hat{q}'; \hat{w}', \hat{Y}')}\right) = \hat{q}'\tilde{Z}\left(\alpha', \frac{\ell^*(\hat{q}; \hat{w}, \hat{Y})}{\ell^*(\hat{q}'; \hat{w}', \hat{Y}')} \frac{\ell'}{\ell^*(\hat{q}; \hat{w}, \hat{Y})}\right)$$

with $\hat{w}' = \hat{w}$, $\hat{Y}' = \hat{Y}$; and that $\ell^*(\hat{q}; \hat{w}, \hat{Y})/\ell^*(\hat{q}'; \hat{w}', \hat{Y}') = \hat{q}/\hat{q}'$ yields

$$\hat{Z}(\hat{q}', \alpha', \ell') = \hat{q}'\tilde{Z}\left(\alpha', \frac{\hat{q}}{\hat{q}'}\tilde{\ell}'\right)$$

for $\hat{q}' = \hat{q}/(1 + g_q)$ and $\hat{q}' = (1 + \lambda_I)\hat{q}/(1 + g_q)$.

C Details of computation

The computation solution consists of first guessing the values of the relevant aggregate variables, solving for the value function and the stationary distribution of firms, and then updating the guess. The procedure is as follows.

1. Construct a grid for productivity $\hat{q}$ and labor $\tilde{\ell}$. We use a log grid for $\hat{q}$ with 100 points between 0 and 10^9. For $\tilde{\ell}$, we use a linear grid with 20 points.

2. Compute the innovation from entrants and the value from entry consistent with the free entry condition

$$x_E^* = \left(\frac{\phi}{\theta_E(\gamma - 1)}\right)^{\frac{1}{\gamma}},$$

$$\hat{\hat{V}}_E = \frac{\gamma\theta_E}{\beta} {x_E}^{\gamma-1}.$$

3. Guess $\hat{Y}$, $\hat{w}$, m, and g. Given m, we can calculate the value of μ by $\mu = X_E = mx_E^*$.

4. Solve for the value function by iterating on the value function and using linear interpolation between grid points.

5. Using the optimal decision rules, solve for the stationary distribution $f(\hat{q}, \alpha, \tilde{\ell})$ by iterating over the density.

6. Then check if the equilibrium conditions are verified. The four conditions are the following

(a) Aggregate output

$$\hat{Y} = \left(\int \int \alpha^{\psi} [\Omega(\hat{w}, \hat{Y}) \mathcal{L}'(\alpha, \tilde{\ell})]^{1-\psi} \int \hat{q} f(\hat{q}, \alpha, \tilde{\ell}) d\hat{q} d\alpha d\tilde{\ell} \right)^{\frac{1}{1-\psi}}$$

(b) Resource constraint

$$\hat{Y} = \hat{C} + \hat{R},$$

with $\hat{C} = \hat{w}/\xi$ and $\hat{R} = \theta_I \int \int \mathcal{X}_I(\alpha, \tilde{\ell})^{\gamma} \int \hat{q} f(\hat{q}, \alpha, \tilde{\ell}) d\hat{q} d\alpha d\tilde{\ell} + m(\phi + \theta_E x_E^{\gamma})$

(c) Consistency condition for productivity

$$\frac{1}{N} \int \int \int \hat{q} f(\hat{q}, \alpha, \tilde{\ell}) d\alpha d\ell dq = 1$$

(d) Free-entry condition

$$\hat{\hat{V}}_E = \frac{\gamma \theta_E}{\beta} x_E{}^{\gamma-1}$$

where[52]

$$\hat{\hat{V}}_E = \int \tilde{Z}(\alpha, 0) \omega(\alpha) d\alpha \left[N + (1-N) \int h(\hat{q}) d\hat{q} \right] (1 + \lambda_E)/(1 + g_q).$$

We use condition (a) to update the value for $\hat{w}$. When $\hat{w}$ is too high, aggregate output implied by the firms decision is too low. We use condition (b) to update the value for $\hat{Y}$. If $\hat{Y}$ is too high then the resource constraint is not satisfied. We update g_q using condition (c). Intuitively, when g_q is too small, the stationary density $f(\hat{q}, \alpha, \tilde{\ell})$ implies the values of $\hat{q}$ that are too large. To update the value of m we use condition (d). Because a large m implies a large μ, which in turn lowers $\tilde{Z}$. Thus the value of m affects the computed value of $\hat{\hat{V}}_E$, through $\tilde{Z}$.

7. Go back to Step 3, until convergence.

[52]Computed from

$$\begin{aligned} \hat{\hat{V}}_E &= \int \left[\int \hat{Z}((1+\lambda_E)\hat{q}/(1+g_q), \alpha, 0)(\bar{f}(\hat{q}) + (1-N)h(\hat{q})) d\hat{q} \right] \omega(\alpha) d\alpha \\ &= \int \left[\int \hat{q} \tilde{Z}(\alpha, 0)(1+\lambda_E)/(1+g_q)(\bar{f}(\hat{q}) + (1-N)h(\hat{q})) d\hat{q} \right] \omega(\alpha) d\alpha \end{aligned}$$

D Robustness checks

D.1 Smaller innovation advantage of entrants

We assess the robustness of the results to a smaller innovative advantage of entrants. In the baseline, we set $(1 + \lambda_E)/(1 + \lambda_I) = 2$ in line with the ratio of the number of patent citations of entrants over that of incumbents. Given the value of λ_I, the baseline calibration implies $\lambda_E/\lambda_I = 6$. An alternative interpretation of the relative citation rate of entrants is to set $\lambda_E/\lambda_I = 2$. We therefore solve the model for $\lambda_E = 2\lambda_I$, where λ_I is kept at the same value as in the baseline calibration. As an additional robustness check, we also report the results for the case where the entrants and the incumbents have the same innovative step, that is $\lambda_E = \lambda_I$. The other parameters, reported in Table 9, are set as described in Section 4.1.[53] We find that the consequences of the firing tax for entrants and incumbents are qualitatively robust to these changes in the calibration. As in the baseline calibration, the firing tax leads to higher innovation rates for incumbents and lower innovation from entrants. The overall effect of the firing tax on growth is however sensitive to the exact calibration.

The results when entrants have a lower innovative advantage are reported in Table 7. As in the baseline calibration, firing costs lead incumbents to increase their innovation rate whereas the innovation by entrants is reduced. The overall negative effect of firing costs on the growth rate is reduced when entrants have a lower innovative advantage. The growth rate of output declines only by 0.01 percentage point when $\lambda_E = 2\lambda_I$, and it even rises slightly relative to the frictionless benchmark when when $\lambda_E = \lambda_I$. When entrants have a lower innovative advantage they also account for a smaller share of aggregate productivity growth, which dampens the consequences of the decline in entry on growth. This calibration shows that the contribution of entrants to aggregate productivity growth is key for the consequences of the firing tax on aggregate productivity growth.

D.2 Smaller innovation steps

In the benchmark calibration, the size of the innovation step λ_I is set at 0.25 following estimates by Bena et al. (2015). In this section we adopt an alternative strategy and use data on the establishment-level employment dynamics to calibrate this parameter. We set λ_I to match the relative proportion of establishments creating jobs and destroying jobs. We measure the relative proportion of establishments creating and destroying jobs

[53] We reset θ_I, ϕ, ε and δ to match the same targets as the baseline.

from the BLS annual Business Employment Dynamics Data and find a ratio of 1.05.[54] The innovation step of the incumbents is closely related to this statistic. For a given growth rate g_q, a smaller λ_I implies a higher innovation probability x_I and hence a larger proportion of establishment creating jobs. In fact, the same growth rate can be reached either with a high λ_I and low x_I or a low λ_I and high x_I. To match the ratio of the relative proportion of establishments creating jobs we set λ_I at 0.0832, which is lower than the baseline value. We continue to assume $\lambda_E = 6\lambda_I$, hence λ_E is also lower than in the baseline. The rest of the parameters are set following the same strategy as in the baseline. The parameters and the targeted statistics are in Tables 9 and 10.

We report the results of this calibration in Table 8. As expected, with the lower innovation step λ_I, the incumbents' probability to innovate is higher than in the baseline. On average, 48% of incumbents innovate in a given year compared with 8.4% in the baseline calibration. Overall the results are *qualitatively* robust to this alternative calibration strategy. The firing tax leads to a decline in average productivity, an increase in the innovation of incumbents and to a reduction in the innovation of entrants. *Quantitatively*, the results are also very similar to the baseline for average productivity. The quantitative effects of the firing tax on the growth rate, however, differ from the baseline. We find that the growth rate of aggregate productivity is virtually unaffected by the firing tax. This smaller negative effect of the firing tax on the growth rate comes here again from the smaller contribution of entrants to the growth rate. Despite the higher innovation advantage of entrants ($\lambda_E = 6\lambda_I$), the contribution of entrants to the growth rate is lower than in the baseline. The decline in the entry rate has therefore less impact on aggregate productivity growth. The results of this calibration are very similar to the case where $\lambda_E = 2\lambda_I$. Note that the two calibrations have very close values for λ_E. In the end, these calibrations suggest that the key parameter for the overall effect of the firing tax on productivity growth is λ_E rather than λ_E/λ_I.

E Further details on the extensions of Section 5

E.1 Extension 1: persistent exogenous shocks

This section complements section 5.1 by giving more details on the calibration of the extension with persistent transitory shocks.

[54] We compute the average share of expanding establishments over the average share of contracting establishments over the available period (March 1994-March 2015). The data are publicly available at https://www.bls.gov/bdm/bdmann.htm.

Table 7: Robustness: innovative advantage of entrants

	Baseline		$\lambda_E = 2\lambda_I$		$\lambda_E = \lambda_I$	
	$\tau = 0.0$	$\tau = 0.3$	$\tau = 0.0$	$\tau = 0.3$	$\tau = 0.0$	$\tau = 0.3$
Growth rate of output g (%)	1.48	1.40	1.48	1.47	1.48	1.51
Innovation probability: incumbents $\bar{x}_I$	0.084	0.09	0.162	0.174	0.202	0.216
Innovation probability: entrants x_E	0.143	0.143	0.508	0.508	1.0	1.0
Creative destruction rate μ (%)	2.65	2.34	4.46	3.79	5.35	4.58
Employment L	100	98.7	100	98.6	100	98.4
Normalized output $\hat{Y}$	100	98.1	100	98.0	100	97.8
Normalized average productivity $\hat{Y}/L$	100	99.3	100	99.3	100	99.4
Number of active products N	0.964	0.956	0.98	0.977	0.982	0.979
Job creation rate (%)	17.0	4.9	17.0	5.2	17.0	5.7
Job creation rate from entry (%)	6.4	4.4	6.4	4.4	6.4	4.5
Job destruction rate (%)	17.0	4.9	17.0	5.2	17.0	5.7
Job destruction rate from exit (%)	2.8	2.4	4.6	3.9	5.5	4.7
R&D ratio R/Y (%)	11.5	10.7	12.0	11.2	12.2	11.6

Note: L, $\hat{Y}$, and $\hat{Y}/L$ are set at 100 in the baseline simulation.

Table 8: Robustness: smaller innovation steps

	Baseline		Small λ_I	
	$\tau = 0.0$	$\tau = 0.3$	$\tau = 0.0$	$\tau = 0.3$
Growth rate of output g (%)	1.48	1.40	1.480	1.477
Innovation probability: incumbents $\bar{x}_I$	0.084	0.09	0.483	0.534
Innovation probability: entrants x_E	0.143	0.143	1.000	1.000
Creative destruction rate μ (%)	2.65	2.34	4.50	3.62
Employment L	100	98.7	100	98.8
Normalized output $\hat{Y}$	100	98.1	100	98.2
Normalized average productivity $\hat{Y}/L$	100	99.3	100	99.4
Number of active products N	0.964	0.956	0.988	0.985
Job creation rate (%)	17.0	4.9	17.01	4.61
Job creation rate from entry (%)	6.4	4.4	6.40	4.13
Job destruction rate (%)	17.0	4.9	17.01	4.60
Job destruction rate from exit (%)	2.8	2.4	4.55	3.67
R&D ratio R/Y (%)	11.5	10.7	11.95	10.85

Note: L, $\hat{Y}$, and $\hat{Y}/L$ are set at 100 in the baseline simulation.

E.1.1 Calibration

We use the variance and autocovariance of establishment-level employment growth to identify the size of the shock ε and the persistence parameter ρ. To give the intuition behind this strategy, let us assume that instead of following a discrete-valued Markov process, the exogenous productivity α follows an AR(1) process (in logs), that is $\ln \alpha_t = \varphi \ln \alpha_{t-1} + u_t$ where u_t is i.i.d. with mean zero and variance σ_u^2. This assumption simplifies the expression of the variance and covariance of log employment changes. In the absence of firing costs, the employment of the firm is given by $\ell = \left(\frac{1-\psi}{\hat{w}}\right)^{\frac{1}{\psi}} \alpha \hat{q} \hat{Y}$, the variance of log employment changes is then $V(\ln \ell_t - \ln \ell_{t-1}) = V(\ln \alpha_t - \ln \alpha_{t-1} + \ln \hat{q}_t - \ln \hat{q}_{t-1})$. Abstracting from the correlation between x_{It-1} and α_{t-1}, we can write the variance of log employment changes as a function of the variance of the changes in the endogenous productivity $\hat{q}_t$ and that of changes in the exogenous productivity α_t. Using the AR(1) assumption, we get

$$V(\ln \ell_t - \ln \ell_{t-1}) = \frac{2(1-\varphi)}{1-\varphi^2}\sigma_u^2 + V(\ln \hat{q}_t - \ln \hat{q}_{t-1}).$$

The covariance of log employment changes can be written as a function of the variance of α and the persistence parameter:

$$Cov(\ln \ell_t - \ln \ell_{t-1}, \ln \ell_{t-1} - \ln \ell_{t-2}) = -\frac{(1-\varphi)^2}{1-\varphi^2}\sigma_u^2.$$

Given the variance of endogenous productivity $V(\ln \hat{q}_t - \ln \hat{q}_{t-1})$, we can infer the variance of the innovation σ_u^2 and the persistence parameter φ from these two statistics. Similarly, when α follows a Markov chain, the variance and the covariance of log employment changes can be used to infer the size of the shock ε and the persistence parameter ρ. The full calibration is reported in Table 9 and the comparison with the models targets are given in Table 10.

E.1.2 Data

We estimate the variance and covariance of annual log employment changes using US census microdata from the Longitudinal Business Database (LBD). The LBD is an exhaustive establishment-level dataset which covers nearly all the non-farm private economy. The dataset provides longitudinally linked data on employment and payroll data for 21 million establishments over 1976-2000. The dataset is constructed using information

Table 9: Alternative calibrations

	Parameter	Persistent α	$\lambda_E = 2\lambda_I$	$\lambda_E = \lambda_I$	Small λ_I
Discount rate	β	0.947	0.947	0.947	0.947
Disutility of labor	ξ	1.475	1.483	1.487	1.482
Demand elasticity	ψ	0.200	0.2	0.2	0.2
Innovation step: entrants	λ_E	1.500	0.50	0.25	0.49912
Innovation step: incumbents	λ_I	0.250	0.25	0.25	0.08319
Innovation cost curvature	γ	2.000	2.0	2.0	2.0
Innovation cost: entrants	θ_E	7.995	1.2560	0.4832	0.41725
Innovation cost: incumbents	θ_I	1.333	0.6280	0.4832	0.06954
Entry cost	ϕ	0.164	0.3243	0.5477	0.85018
Exogenous exit rate	δ	0.001	0.00090	0.00097	0.00056
Transitory shock: size	ε	0.564	0.245	0.234	0.25947
Transitory shock: persistence	ρ	0.718	N/A	N/A	N/A
Avg productivity from inactive lines	h mean	0.976	0.976	0.976	0.976
Firing tax	τ	0.000	0.0	0.0	0.0

Table 10: Comparison between model outcome and the targets

	Data	Model			
		Persistent α	$\lambda_E = 2\lambda_I$	$\lambda_E = \lambda_I$	Small λ_I
Growth rate of output g (%)	1.48	1.48	1.48	1.48	1.48
Employment L	0.613	0.613	0.613	0.613	0.613
Tail index κ	1.06	.	1.06	1.06	1.06
Job creation rate (%)	17.0	.	17.0	17.0	17.0
Job creation rate from entry (%)	6.4	6.4	6.4	6.4	6.4
Variance of employment growth	0.24	0.24	.	.	.
Auto-cov. of employment growth	-0.05	-0.05	.	.	.
Positive employment growth	1.05	.	.	.	1.04

Note: The growth rate and employment targets are computed using BEA and BLS data; for the tail index, we use Axtell (2001)'s estimate; the job flows data are computed from the Census Bureau BDS dataset and the variance and autocovariance of employment growth are measured from LBD micro data. "Positive employment growth" refers to the ratio of expanding private sector establishments over contracting establishments computed from the BLS BED dataset. Missing points indicate that the statistic is not used as a target in the calibration.

from the business register, economic censuses and surveys.[55] We used the Synthetic LBD (U.S. Census Bureau, 2011) which is accessible through the virtual RDC. The results were then validated with the Census Bureau. We compute the variance and covariance of annual log employment change over the period 1976-2000 after excluding the three-digit SIC sectors 100 and 800 to 999. The estimated variance is 0.24 and the covariance is -0.05.

E.2 Extension 2: smaller entrants and the deviation from Gibrat's law

This section provides the details on the analysis of Section 5.2.

E.2.1 Model setup

The (normalized) value of a firm at the beginning of period is

$$\hat{Z}(\hat{q}, \alpha, \ell) = (1-\delta)\hat{V}^s(\hat{q}, \alpha, \ell) + \delta\hat{V}^o(\ell),$$

where

$$\hat{V}^o(\ell) = -\tau\hat{w}\ell$$

is the value of exit. The value of survival is

$$\hat{V}^s(\hat{q}, \alpha, \ell) = \max_{\ell' \geq 0, x_I} \left\{ \hat{\Pi}(\hat{q}, \alpha, \ell, \ell', x_I) + \beta \left((1 - u(\hat{q}))\hat{S}\left(x_I, \frac{\hat{q}}{1+g_q}, \ell' \right) - u(\hat{q})\tau\hat{w}\ell' \right) \right\},$$

where

$$\hat{S}\left(x_I, \frac{\hat{q}}{1+g_q}, \ell' \right) = (1 - x_I)E_{\alpha'}\left[\hat{Z}\left(\frac{\hat{q}}{1+g_q}, \alpha', \ell' \right) \right] + x_I E_{\alpha'}\left[\hat{Z}\left(\frac{(1+\lambda_I)\hat{q}}{1+g_q}, \alpha', \ell' \right) \right].$$

The period profit is

$$\hat{\Pi}(q, \alpha, \ell, \ell', x_I) = ([\alpha\hat{q}]^{\psi}\ell'^{-\psi}\hat{Y}^{\psi} - \hat{w})\ell' - \theta_I(\hat{q})\hat{q}{x_I}^{\gamma} - \tau\hat{w}\max\langle 0, \ell - \ell' \rangle.$$

For the entrants, the free entry condition is

$$\max_{x_E} \left\{ -\theta_E {x_E}^{\gamma} - \phi + \beta x_E \hat{\hat{V}}_E \right\} = 0,$$

[55] For a detailed description of the dataset, see https://www.census.gov/ces/dataproducts/datasets/lbd.html.

where x_E satisfies the optimality condition

$$\beta\hat{\tilde{V}}_E = \gamma\theta_E {x_E}^{\gamma-1}.$$

The expected benefit of entry, $\hat{\tilde{V}}_E$, is now calculated from

$$\hat{\tilde{V}}_E = \int \left[\int \hat{Z}\left(\frac{(1+\lambda_E)\hat{q}}{1+g_q}, \alpha, 0\right) (Np(\hat{q}) + (1-N)h(\hat{q}))d\hat{q} \right] \omega(\alpha)d\alpha.$$

E.2.2 Transformed model and computation

Define the frictionless level of employment without temporary shock as

$$\ell^*(\hat{q};\hat{w},\hat{Y}) \equiv \arg\max_{\ell'}([\alpha\hat{q}]^{\psi}\ell'^{-\psi}\hat{Y}^{\psi} - \hat{w})\ell'$$

with $\alpha = 1$; that is,

$$\ell^*(\hat{q};\hat{w},\hat{Y}) = \left(\frac{1-\psi}{\hat{w}}\right)^{\frac{1}{\psi}} \hat{q}\hat{Y}.$$

Also define $\Omega(\hat{w},\hat{Y})$ by

$$\Omega(\hat{w},\hat{Y}) \equiv \frac{\ell^*(\hat{q};\hat{w},\hat{Y})}{\hat{q}}.$$

In addition, define the deviation of employment from the frictionless level by

$$\tilde{\ell} \equiv \frac{\ell}{\ell^*(\hat{q};\hat{w},\hat{Y})}.$$

Similarly, let

$$\tilde{\ell}' \equiv \frac{\ell'}{\ell^*(\hat{q};\hat{w},\hat{Y})}.$$

Then, the period profit can be rewritten as

$$\hat{\Pi}(\hat{q},\alpha,\ell,\ell',x_I) = \left(\left[\frac{\alpha}{\Omega(\hat{w},\hat{Y})}\right]^{\psi} \tilde{\ell}'^{-\psi}\hat{Y}^{\psi} - \hat{w} \right) \hat{q}\Omega(\hat{w},\hat{Y})\tilde{\ell}' - \theta_I(\hat{q})\hat{q}{x_I}^{\gamma} - \tau\hat{w}\max\langle 0, \hat{q}\Omega(\hat{w},\hat{Y})\tilde{\ell} - \hat{q}\Omega(\hat{w},\hat{Y})\tilde{\ell}'\rangle.$$

Thus this is linear in $\hat{q}$, and can be rewritten as $\hat{q}\tilde{\Pi}(\alpha,\tilde{\ell},\tilde{\ell}',x_I)$, where

$$\tilde{\Pi}(\alpha,\tilde{\ell},\tilde{\ell}',x_I) \equiv \left(\left[\frac{\alpha}{\Omega(\hat{w},\hat{Y})}\right]^{\psi} \tilde{\ell}'^{-\psi}\hat{Y}^{\psi} - \hat{w} \right) \Omega(\hat{w},\hat{Y})\tilde{\ell}' - \theta_I(\hat{q}){x_I}^{\gamma} - \tau\Omega(\hat{w},\hat{Y})\hat{w}\max\langle 0, \tilde{\ell} - \tilde{\ell}'\rangle.$$

Although the value function is not linear in $\hat{q}$, we still utilize the transformation on ℓ by defining the new value functions (abusing the $\tilde{}$ notation on the value functions) as

$$\tilde{Z}(\hat{q},\alpha,\tilde{\ell}) = (1-\delta)\tilde{V}^s(\hat{q},\alpha,\tilde{\ell}) + \delta\tilde{V}^o(\hat{q},\tilde{\ell}),$$

where

$$\tilde{V}^o(\hat{q},\tilde{\ell}) = -\tau\hat{w}\hat{q}\Omega(\hat{w},\hat{Y})\tilde{\ell}.$$

$$\tilde{V}^s(\hat{q},\alpha,\tilde{\ell}) = \max_{\tilde{\ell}'\geq 0, x_I} \left\{\hat{q}\tilde{\Pi}(\alpha,\tilde{\ell},\tilde{\ell}',x_I) + \beta\left((1-u(\hat{q}))\tilde{S}\left(x_I,\frac{\hat{q}}{1+g_q},\tilde{\ell}'\right) - u(\hat{q})\tau\hat{w}\hat{q}\Omega(\hat{w},\hat{Y})\tilde{\ell}'\right)\right\},$$

where

$$\tilde{S}\left(x_I,\frac{\hat{q}}{1+g_q},\tilde{\ell}'\right) = (1-x_I)E_{\alpha'}\left[\tilde{Z}\left(\frac{\hat{q}}{1+g_q},\alpha',(1+g_q)\tilde{\ell}'\right)\right] + x_I E_{\alpha'}\left[\tilde{Z}\left(\frac{(1+\lambda_I)\hat{q}}{1+g_q},\alpha',\frac{(1+g_q)\tilde{\ell}'}{1+\lambda_I}\right)\right],$$

where the transformation of $\tilde{\ell}'$ is similar to the baseline case.

For a given $\tilde{\ell}'$, x_I can be solved from the first-order condition

$$\gamma\theta_I(\hat{q})\hat{q}x_I^{\gamma-1} = \Gamma_I,$$

where

$$\Gamma_I \equiv \beta(1-u(\hat{q}))\left\{E_{\alpha'}\left[\tilde{Z}\left(\frac{(1+\lambda_I)\hat{q}}{1+g_q},\alpha',\frac{(1+g_q)\tilde{\ell}'}{1+\lambda_I}\right)\right] - E_{\alpha'}\left[\tilde{Z}\left(\frac{\hat{q}}{1+g_q},\alpha',(1+g_q)\tilde{\ell}'\right)\right]\right\}.$$

The expected benefit of entry, $\hat{\tilde{V}}_E$, is calculated with the same formula as above

$$\hat{\tilde{V}}_E = \int\left[\int \tilde{Z}\left(\frac{(1+\lambda_E)\hat{q}}{1+g_q},\alpha,0\right)(Np(\hat{q}) + (1-N)h(\hat{q}))d\hat{q}\right]\omega(\alpha)d\alpha,$$

because $\tilde{\ell}=0$ is equivalent to $\ell=0$.

The computational steps are similar to the baseline model. The only difference is that we need to guess $\bar{f}(\hat{q})$ before performing the optimization. We update the guess at the same time as we update the aggregate variables. (It can also be done within the aggregate variables loop.) The following are the steps:

1. First, several variables can be computed from parameters. First, calculate x_E^* from

$$x_E^* = \left(\frac{\phi}{\theta_E(\gamma-1)}\right)^{\frac{1}{\gamma}}.$$

2. Then $\hat{\hat{V}}_E$ can be computed from

$$\hat{\hat{V}}_E = \frac{\gamma\theta_E}{\beta} {x_E}^{\gamma-1}.$$

3. Start the iteration. Guess $\hat{Y}$, $\hat{w}$, m, and g. Guess $\bar{f}(\hat{q})$.

   Given m, we can calculate the value of μ by $\mu = X_E = m x_E^*$. From $\bar{f}(\hat{q})$ and μ, we can obtain $u(\hat{q})$ and $p(\hat{q})$. (The value of N can still be calculated by the same formula as in the baseline case.)

   Now we are ready to solve the Bellman equation for the incumbents. We have two choice variables, $\tilde{\ell}'$ and x_I. The first-order condition for x_I is

$$\gamma\theta_I(\hat{q})\hat{q}x_I^{\gamma-1} = \Gamma_I,$$

   and thus x_I can be computed from

$$x_I = \left(\frac{\Gamma_I}{\gamma\theta_I(\hat{q})\hat{q}}\right)^{1/(\gamma-1)},$$

   where

$$\Gamma_I \equiv \beta(1-u(\hat{q}))\left\{E_{\alpha'}\left[\tilde{Z}\left(\frac{(1+\lambda_I)\hat{q}}{1+g_q}, \alpha', \frac{(1+g_q)\tilde{\ell}'}{1+\lambda_I}\right)\right] - E_{\alpha'}\left[\tilde{Z}\left(\frac{\hat{q}}{1+g_q}, \alpha', (1+g_q)\tilde{\ell}'\right)\right]\right\}.$$

   We can see that x_I is uniquely determined once we know $\tilde{\ell}'$. Let the decision rule for $\tilde{\ell}'$ be $\mathcal{L}'(\hat{q}, \alpha, \tilde{\ell})$. Then $x_I = \mathcal{X}_I(\hat{q}, \alpha, \tilde{\ell})$.

4. Once all decision rules are computed, we can find $f(\hat{q}, \alpha, \tilde{\ell})$ by iterating over the density.

5. Now, we check if the first guesses are consistent with the solution from the optimization. First $\bar{f}(\hat{q})$ can be calculated from $f(\hat{q}, \alpha, \tilde{\ell})$.

   The values of $\hat{w}$ and

$$\hat{Y} = \left(\int\int\int [\alpha\hat{q}]^{\psi}[\ell^*(\hat{q}; \hat{w}, \hat{Y})\mathcal{L}'(\hat{q}, \alpha, \tilde{\ell})]^{1-\psi} f(\hat{q}, \alpha, \tilde{\ell}) d\hat{q} d\alpha d\tilde{\ell}\right)^{\frac{1}{1-\psi}}$$

   and

$$\frac{\hat{w}}{\hat{Y} - \hat{R}} = \xi,$$

where

$$\hat{R} = \int\int\int \theta_I \hat{q} \mathcal{X}_I(\hat{q}, \alpha, \tilde{\ell})^\gamma f(\hat{q}, \alpha, \tilde{\ell}) d\hat{q} d\alpha d\tilde{\ell} + m(\phi + \theta_E x_E^\gamma)$$

In order to check the value of g_q, the condition $\frac{1}{N}\int\int\int \hat{q} f(\hat{q}, \alpha, \tilde{\ell}) d\alpha d\ell dq = 1$ is used. Intuitively, when g_q is too small, the stationary density $f(\hat{q}, \alpha, \tilde{\ell})$ implies the values of $\hat{q}$ that are too large.

In order to set m, we look at the free-entry condition. Because a large m implies a large μ, which in turn lowers $\tilde{Z}$. Thus the value of m affects the computed value of $\hat{\tilde{V}}_E$, through $\tilde{Z}$. Recall that

$$\hat{\tilde{V}}_E = \frac{\gamma \theta_E}{\beta} {x_E}^{\gamma - 1}$$

has to be satisfied, and this has to be equal to

$$\hat{\tilde{V}}_E = \int \left[\int \tilde{Z} \left(\frac{(1 + \lambda_E)\hat{q}}{1 + g_q}, \alpha, 0 \right) (Np(\hat{q}) + (1 - N)h(\hat{q})) d\hat{q} \right] \omega(\alpha) d\alpha.$$

6. Go back to Step 3, until convergence.

E.2.3 Calibration

The overall calibration follows similar steps as the baseline case. The values of β, ψ, λ_I, γ, and δ are the same as the baseline model. For ξ, we target $L = 0.61$ as in the baseline case. The values ϕ and ε are set so that the model generates the amount of overall job creation rate and the job creation rate by entrants close to the data. We assume that $\lambda_E = 1.50$. As in the baseline model, the level parameter of incumbent innovation cost, now represented by $\bar{\theta}_I$ in equation (13), is set so that the overall growth rate of output, g, is 1.48%. We set θ_E so that $\theta_E / \bar{\theta}_I = \lambda_E / \lambda_I$.

The new parameters of this extended model are χ_1 and χ_2 in equation (12) and χ_3 and χ_4 in equation (13). The value of χ_1 is set as a large number so that the size of entrants becomes closer to the data. Given the job creation rate from entrants, the size of entrants is reflected in the entry rate. A large value of χ_1 makes the size of entrants small, and thus increases the entry rate for a given job creation rate by entrants. The value of χ_3 relates to the speed of growth by a small firm, and thus is reflected in the size distribution of firms for small firms. The other two parameters, χ_2 and χ_4, also have effects on the size distribution of firms. Thus, these parameters are picked so that the size distribution of firms is close to the data. The parameter values are summarized in

Table 11: Calibration

	Parameter	Extension
Discount rate	β	0.947
Disutility of labor	ξ	1.5
Demand elasticity	ψ	0.2
Innovation step: entrants	λ_E	1.50
Innovation step: incumbents	λ_I	0.25
Innovation cost curvature	γ	2.0
Innovation cost level: entrants	θ_E	12.492
Innovation cost level: incumbents	$\bar{\theta}_I$	2.082
Entry cost	ϕ	0.022
Exogenous exit (depreciation) rate	δ	0.001
Transitory shock	ε	0.258
Weight function parameter	χ_1	10.0
Weight function parameter	χ_2	10.0
θ_I function parameter	χ_3	0.8
θ_I function parameter	χ_4	1.0
Firing tax	τ	0.0

Table 11.

Table 12 compares the size distribution of firms in the data, the baseline model, and the extended model. The extended model is very close to the data.

Table 13 describes the outcomes of the models for $\tau = 0$ in the baseline model and the extended models. The discrepancy in the entry rate between the model and the data is substantially smaller in the extended model. While it is not perfect, this seems to be the closest we can achieve given the functional forms. What is important here is that the results and their intuitions remain the same with these modifications that make the model outcome closer to the data.

Table 12: Size distribution, Comparison between the US data and the model outcome

	Data	Baseline	Extension
0-4	0.495	0.917	0.467
5-9	0.223	0.017	0.265
10-19	0.138	0.020	0.142
20-49	0.089	0.025	0.090
50-99	0.030	0.009	0.019
100-249	0.017	0.006	0.012
250-499	0.004	0.002	0.003
500-999	0.002	0.001	0.001
1000+	0.001	0.001	0.001

Note: The establishment size distribution is computed from the US Census BDS dataset (average over 1976-2012).

Table 13: Comparison between the US data and the model outcome

	Data	Baseline	Extension
Growth rate of output g (%)	1.48	1.48	1.48
Employment L	0.61	0.60	0.61
Job creation rate (%)	17.0	17.0	17.2
Job creation rate from entry (%)	6.4	6.4	7.5
Job destruction rate (%)	15.0	17.0	17.2
Job destruction rate from exit (%)	5.3	2.8	3.2
Entry rate (%)	12.6	2.8	6.4
R&D spending ratio (R/Y)(%)		11.5	11.8

Note: The growth rate and employment targets are computed using BEA and BLS data and the job flows data are computed from the Census Bureau BDS dataset.

F Empirical analysis

F.1 Data

This section describes the data and the sources used in the empirical analysis reported in Section 6.

R&D spending (R&D): We use data on R&D business expenditures by industry and by country from the OECD ANBERD database (Analytical Business Enterprise Research and Development). The data are available at the two-digit ISIC Rev.3 level and are classified in industries according to the main activity of the enterprise carrying out the R&D. We remove the financial intermediation sector from the dataset. The ANBERD dataset includes statistical estimates which leads to fewer missing values and more extensive time series than the raw data. The ANBERD dataset covers 32 OECD countries and 6 non-member countries between 1987 and 2011, with gaps and breaks in some of the series. We compute R&D as R&D business expenditures divided by the gross output of the industry. The gross output data, obtained from the OECD STAN database, is also available at the two-digit ISIC Rev.3 level. As a robustness check we estimate the equation using the raw R&D data published in the BERD database. The BERD, ANBERD and STAN databases are all publicly available at http://stats.oecd.org/.

Employment protection indicator (EPL): We use two indicators of the strictness of employment protection constructed by the OECD. The indicator EPL1 measures the strictness of dismissal regulation for individual dismissal and the indicator EPL2 also includes measures of the strictness of the regulation on collective dismissal.[56] The indicators are constructed from the reading of statutory laws, collective bargaining agreements and case law combined with advice from officials from OECD member coun-

[56] The OECD codes for EPL1 and EPL2 are EPRC_V1 and EPRC_V2.

tries and country experts. The indicators are compiled from scores between 0 and 6 on the notification procedure, the severance pay and the difficulty of dismissal. The indicator EPL1 is available between 1985 and 2013, and EPL2 is available between 1998 and 2013. The dataset covers 34 OECD countries and 38 non OECD countries (for most non OECD countries the series is not available before 2008). The Employment protection indicators are publicly available at http://stats.oecd.org/ and a comprehensive description of the method used to construct the indicator can be found at http://www.oecd.org/els/emp/oecdindicatorsofemploymentprotection.htm.

Layoff rate (layoff): To measure the sensitivity of each industry to firing costs, we use the layoff rate by industry in the US. Dismissal regulation in the US is less strict than in the rest of the countries considered. The US layoff rate can therefore be used as a proxy for the propensity of each industry to lay off workers. Following Bassanini et al. (2009), we estimate the US layoff rate by industry using data from from the 2004 "Displaced workers, Employee, Tenure and Occupational Mobility" supplement of the Current Population Survey (CPS). We measure the layoff rate as the total number of displaced workers in the three years preceding the survey (2001, 2002 and 2003) divided by total employment in the industry in January 2004. A displaced worker is a worker who has lost his job either because of the following reasons: "plant closing", "insufficient work", "position abolished", "seasonal job ended" or "self-operated business failed". We use the Uniform Extract of CPS made available by the Center for Economic and Policy Research (http://ceprdata.org/cps-uniform-data-extracts/cps-displaced-worker-survey/cps-dws-data/). The data are organized according to the 2002 census industry classification. To be consistent with the R&D data, we convert the layoff data into the two-digit ISIC Rev. 3 classification. The correspondence between the two classification is reported in Table 14. Though the exact procedure used to estimate the US layoff rate differs from Bassanini et al. (2009), the two measures are strongly correlated (correlation coefficient of 0.71). We evaluate the robustness of the results to using the US layoff rates computed by Bassanini et al. (2009), which are available in their Web Appendix.

The merged dataset contains data on 27 OECD countries and 19 industries between 1987 and 2009, with breaks and gaps in the series. The 27 countries are: Austria, Belgium, Canada, Czech Republic, Estonia, Finland, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Switzerland, United States. We excluded the primary sectors, the financial intermediation industry, as well as public and personal services (education, health, etc). The 19 industries used are listed in Table

14.

F.2 Additional regressions

We run two additional sets of regressions to check the robustness of our results. First, we check that the results are similar when using the raw R&D data, available in the BERD dataset, instead of the ANBERD dataset. The results are reported in Table 15. As in the baseline regressions, all the regressions give a negative coefficient, though they are not statistically significant.

We also evaluate the robustness of the results to using the layoff rates computed by Bassanini et al. (2009). We report in Table 16. We find that the results are robust to using their measure.

Table 14: CPS-OECD industry classification correspondence

code	CPS label	code	OECD label
4	Construction	F	Construction
5	Nonmetallic mineral product manufacturing	26	Non-metallic mineral products
6	Primary metals and fabricated metal products	27-28	Basic metals and fabricated metal
7	Machinery manufacturing	29	Machinery n.e.c.
8	Computer and electronic product manufacturing	30-33	Electrical and optical equipment
9	Electrical equipment, appliance manufacturing	30-33	Electrical and optical equipment
10	Transportation equipment manufacturing	34-35	Transport equipment
11	Wood products	20	Wood and wood products
12	Furniture and fixtures manufacturing	36-37	Manufacturing, n.e.c.; recycling
13	Miscellaneous and not specified manufacturing	36-37	Manufacturing, n.e.c.; recycling
14	Food manufacturing	15-16	Food and beverages
15	Beverage and tobacco products	15-16	Food and beverages
16	Textile, apparel, and leather manufacturing	17-19	Textiles, wearing app. and leather
17	Paper and printing	21-22	Paper, printing and publ
18	Petroleum and coal products manufacturing	23	Coke, refined petroleum, nuclear fuel
19	Chemical manufacturing	24	Chemicals and chemical products
20	Plastics and rubber products	25	Rubber and plastics
21	Wholesale trade	50-52	Trade
22	Retail trade	50-52	Trade
23	Transportation and warehousing	60-64	Transport, storage and communications
24	Utilities	E	Electricity, gas and water supply
25	Publishing industries (except internet)	60-64	Transport, storage and communications
26	Motion picture and sound recording industries	60-64	Transport, storage and communications
27	Broadcasting (except internet)	60-64	Transport, storage and communications
28	Internet publishing and broadcasting	60-64	Transport, storage and communications
29	Telecommunications	60-64	Transport, storage and communications
30	Internet service providers and data processing services	60-64	Transport, storage and communications
31	Other information services	60-64	Transport, storage and communications
34	Real estate	70-74	Real estate and business services
35	Rental and leasing services	70-74	Real estate and business services
36	Professional and technical services	70-74	Real estate and business services
37	Management of companies and enterprises	70-74	Real estate and business services
38	Administrative and support services	70-74	Real estate and business services
45	Accommodation	H	Hotels and Restaurants
46	Food services and drinking places	H	Hotels and Restaurants

Notes: The CPS classification is the 2002 Census Industry Classification and the OECD classification is ISIC Rev.3.

Table 15: Regression results (raw R&D data)

	EPL1		EPL2	
	[1]	[2]	[1]	[2]
$\text{EPL}_{ct} \times \text{layoff}_j$	−0.0205	−0.0554	−0.208	−0.0802
	(0.103)	(0.0458)	(0.235)	(0.0612)
R-squared	0.096	0.582	0.098	0.582
N	6199	363	3946	363

Notes: The columns refer to different samples: [1] non-balanced panel [2] year=2005. The balanced panel contains data on 18 countries and 19 industries from 1995 to 2005. The non-balanced regression includes industry and country-time fixed effects. The 2005 regression incudes industry and country fixed effects. Robust standard errors in parentheses.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 16: Regression results (Bassanini et al. (2009) layoff data)

	EPL1			EPL2		
	[1]	[2]	[3]	[1]	[2]	[3]
$\text{EPL}_{ct} \times \text{layoff}_j$	-0.122^{***}	-0.0996^{***}	−0.119	-0.225^{**}	-0.174^{***}	−0.157
	(0.0361)	(0.0264)	(0.0974)	(0.0773)	(0.0437)	(0.128)
R-squared	0.362	0.597	0.609	0.321	0.599	0.609
N	5410	2915	320	3514	2120	320

Notes: The columns refer to different samples: [1] non-balanced panel [2] balanced panel [3] year=2005. The balanced panel contains data on 18 countries and 19 industries from 1995 to 2005. The non-balanced and balanced panel regressions include industry and country-time fixed effects. The 2005 regression incudes industry and country fixed effects. Robust standard errors in parentheses.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.