Barriers to Reallocation and Economic Growth: The Effects of Firing Costs

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We study how factors that hinder the reallocation of inputs across firms influence aggregate productivity growth. We extend Hopenhayn and Rogerson's (1993) firm-dynamics model to allow for endogenous innovation. We evaluate the effects of firing taxes on reallocation, innovation, and productivity growth. We find firing taxes can have opposite effects on entrants' and incumbents' innovation, and the overall outcome depends on the relative strengths of these forces. In the entrant-driven growth calibration, firing taxes reduce aggregate productivity growth, whereas aggregate productivity growth increases in the incumbent-driven growth calibration.
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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 as new products and techniques are developed. As documented by Micco and Pagés (2007) and Haltiwanger, Scarpetta and Schweiger (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 both 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 US.

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 not only affect the level of aggregate productivity, but are also likely

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to modify the firms' incentives to innovate. We use a model of innovation-based economic growth to investigate the consequences of firing costs on job reallocation and productivity 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) in which 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 firms' incentives to innovate and hence change the growth rate of the economy.

We model firing costs as a tax and study the effect of this tax 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: Whereas the firing tax tends to reduce entrants' innovation, it may increase the innovation incentives of incumbent firms. The entrants' innovation declines because the tax 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 a firing tax. For those firms, innovating has the added benefit of allowing them to avoid paying the firing tax, because they would no longer need to downsize if the quality of their product were 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 rate at which entrants innovate affects the incumbents' incentive to innovate. By reducing the entry rate, firing costs lower the incumbent's probability of being taken over by an entrant. This

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

decline in the rate of creative destruction increases the expected return of R&D investments and therefore tends to increase the incumbents' innovation (creative-destruction effect).

With the fall in the entrants' innovation rate and the possible increase in the incumbents' innovation rate, the overall effect of the firing tax depends on the importance of the two types of innovation for growth.[2] We consider two calibrations in the quantitative analysis. In the first calibration, which we call *entrant-driven growth*, entry is the main driver of aggregate productivity growth, and the negative effect on entrants dominates. In this case, the firing tax leads to a decrease in the rate of growth of aggregate productivity. In the second calibration, which we call *incumbent-driven growth*, the incumbents' contribution is larger, and the positive effect on incumbents dominates. The firing tax enhances growth with this calibration. Our results illustrate the importance of including the incumbents' innovation in the analysis. The overall effect of firing taxes on growth crucially depends on the incumbents' innovation, even in the entrant-driven growth case: The fall in the growth rate, due to the decrease in the entrants' innovation, is dampened by the response of the incumbents' innovation; ignoring the incumbents' innovation would have thus led to overestimating 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.

To evaluate the magnitude of the possible negative effects of the firing tax, we compare its effects with the effects of a labor tax. We find the negative growth effect of the firing tax in the entrant-driven case is similar to the growth effect of a 5% labor tax. This arguably moderate number, however, does not mean the welfare consequences of the reduction in growth, caused by the firing tax, is small. A back-of-the-envelope calculation suggests that, under this calibration, the growth effect lowers consumer welfare more than the level effect does.

In some recent studies, firing regulations have been shown to have a negative effect on the level but also on the growth rate of aggregate productivity. For example, Autor, Kerr and Kugler (2007) estimate 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. Bassanini, Nunziata and Venn (2009) find firing costs tend to reduce total factor productivity growth in industries where firing costs are more likely to be binding.[3] Meanwhile, some studies, such as Acharya, Baghai and Subramanian (2013) and Ueda and Claessens (2016), find situations in which employment-protection regulations can

[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. Bartelsman, Gautier and Wind (2016) propose a related model and provide evidence that countries with higher firing costs have relatively smaller high-risk innovation sectors.

[3]See also Andrews, Criscuolo and Gal (2015) and Cette, Lopez and Mairesse (2016) for similar results.

have positive effects on innovation and growth. These conflicting results are consistent with our theoretical model, which uncovers various forces that affect the aggregate growth rate in opposite directions. The message of our model is that, in evaluating the growth effects of employment protection, we have to carefully analyze the strengths of the different forces that shape both the composition of innovation and the aggregate growth rate.

Our paper is related to several theoretical papers 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, Mendes Tavares and Restuccia (2016) have shown 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 decreases. 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.[5] Empirical studies that evaluate the contribution of reallocation to productivity changes, such as Foster, Haltiwanger and Krizan (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 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 (2017).[6] In contrast to our study, their focus is, as in the studies cited above, exclusively on the level of aggregate productivity. Samaniego (2006*b*) highlights the effects of firing costs in a model with productivity growth. He considers, however, only exogenous productivity growth and studies how the effects of firing costs differ across industries.[7] Poschke (2009) is one of the few exceptions that studies the effects of firing costs on aggregate productivity growth. In Poschke (2009), firing

[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, Mendes Tavares and Restuccia (2016) analyze a stylized continuous-time model in which firm-level employment can only take two different values, and also find the firing cost reduces aggregate productivity.

[5]For such studies, see, for example, Restuccia and Rogerson (2008) and Hsieh and Klenow (2009).

[6]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 (2017) show that policy distortions that are positively correlated with establishment-level productivity imply larger reductions in aggregate productivity when productivity is endogenous.

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

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. Bertola (1994) is an earlier paper that analyzes the growth effect of firing costs. In his analysis, however, only entrants innovate.

Our paper is also related to the growing literature on innovation and firm dynamics that follows the contribution by Klette and Kortum (2004). In particular, our paper is related to Acemoglu et al. (2013), who 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 (2018), Acemoglu and Cao (2015), and Peters (2016) that consider quality-ladder firm-dynamics models in which 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 in our approach is that we use labor market data to discipline the model parameters, which is consistent with our focus on labor market reallocation and labor market policy.[9] Methodologically, whereas these models are typically written in continuous time, 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 (e.g., Huggett, 1993; Aiyagari, 1994) and standard firm-dynamics models (e.g., Hopenhayn and Rogerson, 1993; Lee and Mukoyama, 2008). Using this method is particularly important for our model, because firing taxes introduce a kink in the return function and make 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 model's fit.

The paper is organized as follows. Section 2 sets up the model. Section 3 provides an analytical characterization of the model. Section 4 describes the quantitative analysis. Section 5 analyzes two extensions of the model and discusses the robustness of the results. Section 6 concludes.

I. Model

We build a model of firm dynamics in the spirit of Hopenhayn and Rogerson (1993). We extend their framework to allow for endogenous firm-level productivity. 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 (2018).

[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, Hsieh and Klenow (2016) also utilize 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.

A continuum of differentiated intermediate goods exists 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-goods sector. We first describe the optimal aggregate consumption choice. We then describe the final-goods 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.

A. *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; 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 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:

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

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

and the second is the optimal labor-leisure choice:

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

B. 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 1, 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 α_{jt} is i.i.d. across time and products.[13] We also assume 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]

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 let 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

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

[12] Similar formulations are used by Luttmer (2007), Acemoglu and Cao (2015), and Akcigit and Kerr (2018), among others.

[13] The i.i.d. assumption across time is relaxed in section IV.A.

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

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 the consumers and the firms engaging in R&D activities combine the intermediate goods on their own.[15] In this sense, the final-goods 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.

C. *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.

We consider two sources of innovations. One is the *innovation by incumbents*: An incumbent can invest in R&D 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.[16] 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 an incumbent. The previous producer is, as a result, forced to exit.[17]

PRODUCTION OF INTERMEDIATE GOODS. — Each product j is produced by the leading-edge monopolist that produces the highest quality for that particular

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

[16] In our model, the only way incumbents can innovate is by improving the quality of the products they are currently producing. Although we do not explicitly model the creative destruction by incumbents, one can interpret this margin as being captured by the entry component. In this model, a unit of production ("a firm") is a single product line. Creative destruction from entry here can therefore be interpreted as the displacement caused by the innovation of both new firms and incumbent firms (when they innovate on products they are not currently producing). Assuming incumbent firms open new establishments when they add a product line, our calibration is consistent with this interpretation. In fact, below, we calibrate the size of the creative-destruction effect, using the job creation by new *establishments*, which includes the opening of new establishments by incumbent firms.

[17] Without this assumption, the entrant may engage in limit-pricing behavior to drive out the incumbents. This assumption is not necessary if the monopoly price set by the entrant is sufficiently small or if the innovative advantage of the entrant is sufficiently high. In our model, the condition for monopoly pricing is $1 + \lambda_E > (1 - \psi)^{-(1-\psi)/\psi}$. Acemoglu and Cao (2015) also derive a similar condition. When this condition is not satisfied, instead of assuming the lower-quality producer automatically exits, we could also resort to a market-participation game with price competition considered in Akcigit and Kerr (2018).

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 the firm must pay the tax τw_t for each worker fired,[18] including when the firm exits.[19]

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.[20]

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 must 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}.[21] 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 the entrants' innovation is not targeted: Each entrant innovates on a randomly selected product. The entrants choose their innovation probability before learning the quality of the product they will innovate upon. An entrant innovates on an existing product

[18] Following the literature (e.g., Hopenhayn and Rogerson, 1993), we assume the firing costs are incurred only when the firm contracts or exits (i.e., only when job destruction occurs). As is well documented (e.g., Burgess, Lane and Stevens, 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.

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

[20] 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 (2018). Kortum (1997) provides empirical support for this assumption in a time-series context.

[21] Bollard, Klenow and Li (2016) provide empirical support for the assumption that entry costs increase with productivity.

with probability N_t, and on an inactive product with probability $1 - N_t$. We assume 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.

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). Although 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.[22]

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.[23]

D. *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 must 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, and at the same time, incumbents choose their employment level and pay the firing costs whenever they contract. The labor market clears and production takes place. The consumer chooses his 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,

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

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

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

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

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

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

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 paying the entry 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, as 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 the firing tax occurs through variation in the mass of potential entrants m_t. 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

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

E. 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.

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. We rewrite the firm's value functions using this expression. Below, we use the hat notation for the stationary value functions to distinguish from the value functions in 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

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

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_q, and μ.

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

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

General equilibrium under balanced growth. — Let the decision rule for x_I be $\mathcal{X}_I(\hat{q}, \alpha, \ell)$, and let 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 $f \rightarrow \mathbf{T}f$, 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 average innovation probability of incumbents is

$$\bar{x}_I = \int\int\int \mathcal{X}_I(\hat{q}, \alpha, \ell)(f(\hat{q}, \alpha, \ell)/N) d\hat{q} d\alpha d\ell.$$

The probability that an incumbent is displaced by an entrant, μ, is equal to the

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

aggregate innovation by entrants:

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

Let us denote $\bar{f}$ as 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:

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

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

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

holds, where $\hat{R} = \int \int \int \theta_I \hat{q} \mathcal{X}_I(\hat{q}, \alpha, \ell)^\gamma f(\hat{q}, \alpha, \ell) + m(\theta_E {x_E}^\gamma + \phi)$ is the normalized R&D spending, which includes the potential entrants' fixed cost, and $\hat{C}$ is given by the labor-leisure decision (2).

II. Characterization of the model

In the absence of firing taxes, the model's solution can be characterized analytically. The frictionless case provides a useful benchmark and gives some insight into the determinants of innovation and growth in the model. The economy without firing taxes is used also to calibrate the model in the quantitative analysis. Characterizing the economy with the firing tax is less straightforward. In this section, we also provide a partial characterization of the model with the firing tax, which facilitates the numerical computation of the equilibrium.

A. 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

$$x_I = \left(\frac{\beta(1-\mu)\lambda_I(\mathcal{A}+\mathcal{B})}{(1+g_q)\gamma\theta_I} \right)^{\frac{1}{\gamma-1}}, \tag{11}$$

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 x_I is constant across firms regardless of the values of α and $\hat{q}$. This result hence implies the expected growth of a firm is independent of its size, which is consistent with *Gibrat's law.*[25] The independence between the firm's growth rate and its size implies the endogenous productivity 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 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 shape parameter κ (i.e., the density has the form $F\hat{q}^{-(\kappa+1)}$), which solves*

$$1 = (1-\delta)\left[(1-\mu)x_I\gamma_I^\kappa + \mu\gamma_E^\kappa + (1-\mu)(1-x_I)\gamma_N^\kappa\right],$$

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*

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

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

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

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, thinking of the policy's effect on growth through these three components – the incumbents' innovation, the entrants' innovation on active products, and the entrants' innovation on inactive products – is still useful.

B. *A characterization of the economy with the firing tax*

With the firing tax, the firm's employment decision is no longer static; therefore, the characterization is not as straightforward as in the case without the firing tax. We can derive a partial characterization, however, that greatly eases the computational burden of the numerical solution method. The main idea is to formulate the model in terms of the deviations from the frictionless outcome. The details of the derivation are in Appendix B.

First, define the *frictionless level of employment with* $\alpha = 1$ as

$$\ell^*(\hat{q};\hat{w},\hat{Y}) \equiv \arg\max_{\ell'}([\hat{q}]^{\psi}\ell'^{-\psi}\hat{Y}^{\psi} - \hat{w})\ell' = [(1-\psi)/\hat{w}]^{\frac{1}{\psi}}\hat{q}\hat{Y}.$$

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 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 the 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
(12)

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

The linearity of the value functions implies

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

also holds.

The optimization problem in (12) has two choice variables: $\tilde{\ell}'$ and x_I. The first-order 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 x_I is uniquely determined once we know $\tilde{\ell}'$. Let the decision rule for $\tilde{\ell}'$ in the right-hand side of (12) be $\mathcal{L}'(\alpha, \tilde{\ell})$. Then the optimal x_I can be expressed as $x_I = \mathcal{X}_I(\alpha, \tilde{\ell})$, which implies that x_I is independent of $\hat{q}$.

III. 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 we analyze the effects of firing taxes on job flows, employment and output levels, and productivity growth.

A. *Computation and calibration*

The details of the computational methods are described in Appendix D. 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 the 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 (e.g., Huggett, 1993; Aiyagari, 1994). This approach separates our work from recent models of innovation and growth, such as Klette and Kortum (2004), Acemoglu et al. (2013), and Akcigit and Kerr (2018), since these models heavily rely on analytical characterizations in a continuous-time setting. Being able to use a standardized numerical method to compute the equilibrium is particularly useful in our experiment because the firing tax introduces a kink in the firm's objective function, which makes obtaining analytical characterizations to the maximization problem difficult.

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 we use US data to compute our targets. In addition to the standard targets that are widely used in the macroeconomics literature, we use establishment-level labor market data to pin down the parameters that relate to the establishment dynamics.[27]

The first set of targets is 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.[28] These estimates indicate 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. Given that little direct evidence is available for pinning down these parameters, we consider two alternatives.

The first approach, which we call *entrant-driven growth*, considers an economy in which the innovations developed by entrants are more radical than those developed by incumbents, that is, $\lambda_E > \lambda_I$.[29] We set $\lambda_E = 1.5$ and $\lambda_I = 0.25$, based on the recent estimates of Bena, Garlappi and Grüning (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.[30] To set the innovation-costs parameters, we assume the innovation cost

[27]Our model does not distinguish between firms and establishments. Because 95% 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.

[28]See, for example, Griliches (1990).

[29]A recent paper that uses this approach is Akcigit and Kerr (2018).

[30]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 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

is proportional to its size, that is, $\theta_E/\theta_I = \lambda_E/\lambda_I$, and thus radical innovations are more costly than incremental ones.

In the second approach, which we call *incumbent-driven growth*, we assume entrants and incumbents have the same innovative step, that is, $\lambda_E = \lambda_I$. This assumption is the one made, for example, by Garcia-Macia et al. (2018). We continue to assume $\theta_E/\theta_I = \lambda_E/\lambda_I$, that is, $\theta_E = \theta_I$. We will see that, in this case, the incumbents account for a larger share of growth than the entrants.

The rest of the parameters is set following the same strategy for both approaches. We set the level of θ_I to match the average growth rate of output per worker. When θ_I is smaller, the probability of innovating 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, more entry occurs; and therefore, the job-creation rate by entrants is larger. We assume the transitory shock α is uniformly distributed and can take three values $\{1-\varepsilon, 1, 1+\varepsilon\}$, with a probability of 1/3 for each value. The value of ε is set to replicate the overall 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.[31] 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 $\hat{q}$.[32] 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.[33] A large δ implies a larger tail index, which indicates a thinner tail.[34] The parameter values of the two calibrations are summarized in Table 1.

Table 2 compares the model outcomes and the targets. Both approaches allow us to match the targets exactly. We also report, in the second part of the table, relevant statistics that are not used as targets. We report the job-destruction rate and job-destruction rate from exit, and we find the incumbent-driven growth calibration delivers a job-destruction rate from exit that is closer to the data.[35] We also report the R&D expenditures as a share of aggregate output. In both

citations at age 25 equals 1.9. We thank the authors for making these data available to us.

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

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

[33]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) report the US estimate of 1.25, along with estimates from other countries.

[34]See section II.A for the expression of the tail index.

[35]The job-destruction rate from exit is matched exactly when $\lambda_E = 1.14\lambda_I$. In section IV.A below, we consider an extended model (with the entrant-driven growth calibration) in which the firm-size distribution is better matched. With the extended model, the entrant-driven growth calibration can deliver a job destruction rate from exit that is closer to the data.

Table 1—: Calibration

	Parameter	Entrant-driven	Incumbent-driven
Discount rate	β	0.947	0.947
Disutility of labor	ξ	1.4747	1.4870
Demand elasticity	ψ	0.2	0.2
Innovation step: entrants	λ_E	1.50	0.25
Innovation step: incumbents	λ_I	0.25	0.25
Innovation cost curvature	γ	2.0	2.0
Innovation cost level: entrants	θ_E	7.992	0.483
Innovation cost level: incumbents	θ_I	1.332	0.483
Entry cost	ϕ	0.1644	0.5477
Exogenous exit (depreciation) rate	δ	0.00100	0.00097
Transitory shock	ε	0.267	0.234
Avg productivity from inactive lines	h mean	0.976	0.976
Firing tax	τ	0.0	0.0

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

		Model	
	Data	Entrant-driven	Incumbent-driven
Growth rate of output g (%)	1.48	1.48	1.48
Employment L	0.613	0.613	0.613
Tail index κ	1.06	1.06	1.06
Job creation rate (%)	17.0	17.0	17.0
Job creation rate from entry (%)	6.4	6.4	6.4
Job destruction rate (%)	15.0	17.0	17.0
Job destruction rate from exit (%)	5.3	2.8	5.5
R&D spending ratio (R/Y) (%)	-	11.5	12.2
Entrants' share of growth	-	0.67	0.22

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.

calibrations, the R&D ratio is larger than what we typically see from conventional measures of R&D spending. Because our model intends to capture 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, comparing the model R&D spending to a statistic broader than the conventional R&D measure is more appropriate. Here, the R&D spending ratio is in line with Corrado, Hulten and Sichel's (2009) estimate of intangible investments in the US.

The 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' innova-

[36]Garcia-Macia, Hsieh and Klenow (2016) use a similar approach to decompose the growth rate of aggregate productivity growth in the US.

tion 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 $[(1-\delta)\lambda_E\mu+\delta((1+\lambda_E)\bar{q}^h-1)]/g_q$. We report the contribution of entrants in the last line of Table 2. In the entrant-driven growth case, entrants account for 67% of the growth rate of aggregate productivity, whereas they account for 22% of growth in the incumbent-driven case.

B. *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 that amounts to 3.6 months of wages, that is, $\tau = 0.3$. The data from the World Bank Doing Business Dataset partly motivated the choice of this level of tax. The Doing Business dataset reports the mandatory severance payments due by firms upon firing a worker.[37] To ensure comparability across countries, precise assumptions are made about the firm and the 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 10 years of tenure. The firing tax, $\tau = 0.3$, corresponds to the median severance payments indicated by the vertical line in Figure 1.[38] This number is a conservative estimate of the median firing costs, because firing costs include not only severance payments, but also the cost related to the length and the complexity of the dismissal procedure.[39] We also report the results for higher values of the firing tax and consider taxes that amount to one year and two years of wages.

Below, we first describe the results and the main intuitions in the entrant-driven growth case. We then turn to the incumbent-driven case. Although the intuitions are similar in the two cases, we will see the growth effect of firing taxes depends on the calibration.

The columns of Table 3 compare the outcomes with and without the firing tax for the entrant-driven growth case. To facilitate the comparison, the variables L, $\hat{Y}$, and $\hat{Y}/L$ are normalized to 100 in the frictionless economy ($\tau = 0.0$). Similarly to Hopenhayn and Rogerson (1993), employment L declines when the firing tax

[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.

[38]This number is also close to the level of firing costs in France, estimated by Kramarz and Michaud (2010) to be 25% of a worker's annual wages. This level of firing tax is somewhat milder than 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 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.

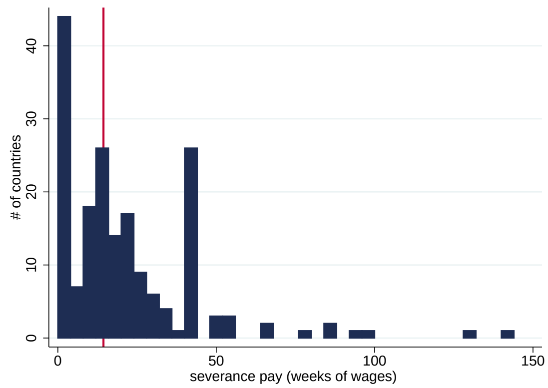


Figure 1. : Severance payments across the world

Note: This figure shows the distribution of severance payments for a worker with 10 years of tenure in the retail industry. The vertical line indicates the median.
Source: Doing Business dataset (2015), World Bank.

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 other hand, being aware of the possibility of facing firing taxes in future, the firm also becomes more reluctant to hire when a good shock occurs. 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, mainly because of *misallocation*: The allocation of labor across firms is not aligned with the firms' productivity when the firms face firing costs because firms do not adjust their labor as much as they would in the frictionless economy. This outcome 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, Scarpetta and Schweiger (2014). Whereas the marginal product of labor is equalized across firms in the frictionless equilibrium, a notable dispersion exists in the marginal product of labor in the economy with the firing tax as shown in Figure 2. The marginal product of labor deviates by more than 5% from the equilibrium wage for about 35% of firms. Entry also decreases with the firing tax. As shown in the Table, the firing tax reduces the number of active intermediate products N, which further reduces the aggregate productivity level. Overall, however, the effect of the firing tax is modest. We find that average productivity is reduced by 0.7% when $\tau = 0.3$.[41]

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

[41]The magnitude is in line with the results found in previous studies. When $\tau = 1$, we find a reduction in average productivity of 1.7%, which is in the same order of magnitude as Hopenhayn and Rogerson

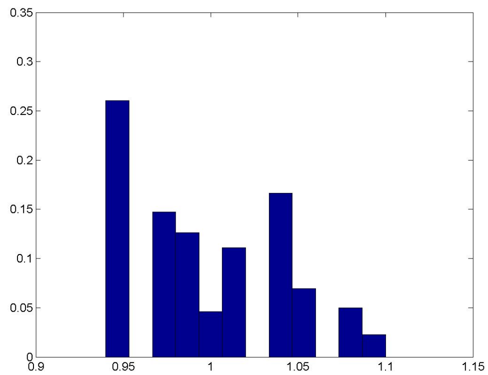


Figure 2. : Misallocation of labor

Note: This figure shows the distribution of the marginal productivity of labor, in the entrant-driven growth calibration, when 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.

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, decreases by about 0.3 percentage points. Two factors reduce the entrants' incentive to innovate. First, the firing tax reduces expected profits because it increases the cost of operating a firm (*direct effect*). Second, firing costs prevent firms from reaching their optimal scale, and this misallocation reduces the entrants' expected profits (*misallocation effect*).

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 mass of potential entrants, m. In other words, here, the reduction of the entrants' incentive to innovate is represented by the reduction of m. Because m is determined in the general equilibrium, the actual mechanics behind the decline in m are somewhat involved. To see the intuition, consider the analytical solution, presented in Appendix B. The model's general equilibrium can be considered a system of two equations with two unknowns. The two equations are the consumer's first-order condition for the labor-leisure choice and the free-entry condition for the intermediate-good firms. The two unknowns are m and L. Given L, the number of potential entrants adjusts such that the free-entry condition is satisfied. A lower m reduces the probability of being displaced, and hence increases firms' expected life span, which increases the value of entry. When the firing tax is imposed, the profitability of entry declines, and hence m is reduced until the value of entry increases back to satisfy the free-entry condition. This effect through the

(1993), who find a reduction in average productivity of 2.1%.

Table 3—: The effects of firing costs: Entrant-driven case

	$\tau = 0.0$	$\tau = 0.3$	$\tau = 1$	$\tau = 2$
Growth rate of output g (%)	1.48	1.39	1.28	1.16
Average innovation probability by incumbents x_I	0.084	0.091	0.108	0.133
Innovation probability by entrants x_E	0.143	0.143	0.143	0.143
Creative-destruction rate μ (%)	2.65	2.30	1.76	1.11
Employment L	100	98.8	98.1	99.5
Normalized output $\hat{Y}$	100	98.1	96.5	96.6
Normalized average productivity $\hat{Y}/L$	100	99.3	98.3	97.0
Number of active products N	0.964	0.958	0.946	0.917
Job-creation rate (%)	17.0	4.7	3.1	1.8
Job-creation rate from entry (%)	6.4	4.3	2.8	1.5
Job-destruction rate (%)	17.0	4.7	3.1	1.8
Job-destruction rate from exit (%)	2.8	2.4	1.9	1.2
R&D ratio R/Y (%)	11.5	10.6	9.2	7.4

Note: L, $\hat{Y}$, and $\hat{Y}/L$ are set at 100 in the $\tau = 0.0$ case.

free-entry condition is the main intuition for how m responds to the firing tax; because m also affects the labor-leisure choice, additional effects are also at work.

In contrast to the entrants' innovation, the incumbents' innovation probability *increases* by about 0.7 percentage points 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 increases the cost of operating the firm, which reduces the profits from innovation. In addition, the misallocation of labor is costly because the firm will not operate at its optimal size after innovating. As for the entrants, both the direct effect and misallocation effect tend to reduce the incumbents' innovation. 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, because they no longer need to reduce their employment (*tax-escaping effect*).[42] In addition, the incumbents' incentives to innovate further depend on the entry rate (*creative-destruction effect*). A lower entry rate reduces the risk of incumbents being taken over by an entrant, which, in turn, increases the return of the firm's R&D investment. In effect, a lower creative-destruction rate increases the incumbents' planning horizon.[43] This effect also can be seen from the expression of x_I in (11). There, the direct effect of μ on x_I is negative for a given g_q.

To assess the importance of the creative-destruction effect, we conduct an additional experiment in the entrant-driven case. In this experiment, we hold the value of the creative destruction rate μ fixed to its frictionless level by not im-

[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]Acemoglu and Cao (2015) make a related observation that, in their model, a policy that discourages entry may increase or reduce the overall growth rate of the economy because of the change in the innovation rate of incumbents.

Table 4—: The effects of firing costs: Fixed entry rate in the entrant-driven case

	$\tau = 0.0$	$\tau = 0.3$	Fixed entry $\tau = 0.3$
Growth rate of output g (%)	1.48	1.39	1.48
Average innovation probability by incumbents x_I	0.084	0.091	0.086
Innovation probability by entrants x_E	0.143	0.143	0.143
Creative-destruction rate μ (%)	2.65	2.30	2.65
Employment L	100	98.8	100.0
Normalized output $\hat{Y}$	100	98.1	99.4
Normalized average productivity $\hat{Y}/L$	100	99.3	99.4
Number of active products N	0.964	0.958	0.964
Job-creation rate (%)	17.0	4.7	5.3
Job-creation rate from entry (%)	6.4	4.3	4.9
Job-destruction rate (%)	17.0	4.7	5.3
Job-destruction rate from exit (%)	2.8	2.4	2.8
R&D ratio R/Y (%)	11.5	10.6	11.6

Note: Note: L, $\hat{Y}$, and $\hat{Y}/L$ are set at 100 in the $\tau = 0.0$ case.

posing 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 already well known, the firing tax creates an inaction zone in the labor decision of the firm. We find the shape of the innovation decision follows closely that of the labor decision. More importantly, the figure shows the firing tax leads firms that are below their optimal size to reduce their innovation probability. As explained above, this negative effect comes both 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 because innovating provides the added benefit of avoiding paying the firing tax.[44] Overall, the results displayed in the last column of Table 4 indicate that those two effects on incumbents largely offset each other. When the entry rate is held constant, the incumbents' innovation increases by only 0.2 percentage points versus 0.7 percentage points in the original experiment. Hence, the decline in entry accounts for two-thirds of the increase in the incumbents' innovation. This result suggests 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 the entrant-driven case, the negative effect on entrants dominates, and results in the reduction of the growth rate. The growth rate of output is 1.39% in the economy with the firing tax $\tau = 0.3$, and

[44]These opposite effects tend to reduce the static misallocation. Because 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, which can reduce the level of misallocation.

Table 5—: The effects of firing costs: Incumbent-driven case

	$\tau = 0.0$	$\tau = 0.3$	$\tau = 1$	$\tau = 2$
Growth rate of output g (%)	1.48	1.51	1.58	1.68
Average innovation probability by incumbents x_I	0.202	0.216	0.242	0.276
Innovation probability by entrants x_E	1.0	1.0	1.0	1.0
Creative-destruction rate μ (%)	5.35	4.58	3.47	1.98
Employment L	100	98.4	96.7	97.3
Normalized output $\hat{Y}$	100	97.8	95.4	95.2
Normalized average productivity $\hat{Y}/L$	100	99.3	98.7	97.8
Number of active products N	0.982	0.979	0.973	0.953
Job-creation rate (%)	17.0	5.7	3.9	2.2
Job-creation rate from entry (%)	6.4	4.4	3.0	1.5
Job-destruction rate (%)	17.0	5.7	3.8	2.1
Job-destruction rate from exit (%)	5.5	4.7	3.6	2.1
R&D ratio R/Y (%)	12.2	11.6	10.7	9.2

Note: L, $\hat{Y}$, and $\hat{Y}/L$ are set at 100 in the $\tau = 0.0$ case.

1.48% without the firing tax. Table 5 compare the outcomes with and without firing taxes in the incumbent-driven case. The level effects are similar to those described in the entrant-driven case. Moreover, in this case also, the firing tax increases the incumbents' innovation while reducing the entrants' innovation. The overall effects on growth are, however, the opposite of the entrants-driven case. In this calibration, the positive effect on the incumbents' innovation dominates, and the firing taxes lead to an increase in the growth rate of aggregate productivity. The growth rate of output is 1.51% in the economy with the firing tax $\tau = 0.3$.

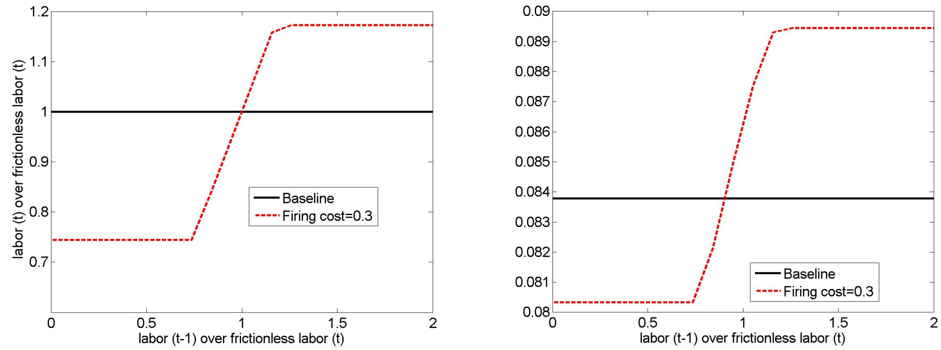
To gauge the impact of the negative growth effect of the firing tax in the entrant-driven case, we compare its magnitude with the well-studied level effect. We conduct a back-of-the-envelope calculation and compute the consumption-equivalent welfare change induced by the growth effect of the firing tax in the entrant-driven growth calibration. The details of the calculation are provided in Appendix C. We find that the growth effect of the firing tax ($\tau = 0.3$), in the entrant-driven case, is equivalent to a permanent drop in consumption of 1.6%, which is larger than the level effect (equivalent to a 0.9% drop in consumption).

IV. Extensions and discussions

In this section, we consider several extensions of our basic model. We describe two extensions in detail and then discuss some more variations of the model. We primarily consider variations around the entrant-driven case; the intuitions are similar across different calibration strategies.

A. Extensions

Our baseline model is intentionally kept simple to deliver sharp insights. Although this simplicity allows us to characterize the model analytically in the



(a) Labor decision (b) Innovation probability

Figure 3. : Labor and innovation decision functions, fixed entry rate in the entrant-driven case

Note: The left panel 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 frictionless value. The right panel displays the firm's innovation decision x_I as a function of the previous labor level $\tilde{\ell}$ when μ is kept constant to its frictionless value. The transitory shock is set to 1 for both panels.

absence of firing costs, it limits the model's ability to fit the data. In this section, we relax some of the simplifying assumptions to improve the fit of the model, and we show these extensions do not alter the paper's main results. In particular, we find our main results are robust to allowing for a persistent transitory shock and for an alternative innovation process that delivers a better fit for firm-dynamics statistics.

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 firing taxes on aggregate productivity. Because the persistence of the shocks affects 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 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.

To incorporate the persistence of the exogenous productivity shock α_t, we now assume α_t follows a Markov chain, with transition probabilities given by

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

where ρ governs the persistence of the process. As in the baseline model, α_t can take three values: $\underline{\alpha}_1 = 1-\varepsilon$, $\underline{\alpha}_2 = 1$, and $\underline{\alpha}_3 = 1+\varepsilon$. To identify ρ and ε, we use the variance and the autocovariance of establishment-level employment 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 whereas 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).[45] 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 this calibration implies not only more persistent shocks, but also larger shocks than in section III. The other parameters, β, ψ, λ_I, λ_E, γ, and δ, are set to the same values as in the entrant-driven growth case of section III, whereas 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 parameter values are reported in Table 1, and the targets are reported in Table 2, both in Appendix E.[46]

We report the results of the model with persistent exogenous shocks in Table 6. 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.

The larger decline in average productivity may be surprising because 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 the 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 tends to increase misallocation. The effects of larger shocks dominate the effects of higher persistence, resulting in a lower average productivity than in section III.

The fact that the calibration leads to larger transitory shocks also matters for the growth effect. Here again, the fact that the exogenous shocks are larger dom-

[45] 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.

[46] Though the overall job-creation rate is not a target in this calibration, it is equal to 17.02%, which is virtually identical to the value in section III.

Table 6—: Persistent exogenous shocks

	Section 4		Persistent α	
	$\tau = 0.0$	$\tau = 0.3$	$\tau = 0.0$	$\tau = 0.3$
Growth rate of output g (%)	1.48	1.39	1.48	1.37
Average innovation probability by incumbents $\bar{x}_I$	0.084	0.091	0.084	0.089
Innovation probability by entrants x_E	0.143	0.143	0.143	0.143
Creative-destruction rate μ (%)	2.65	2.30	2.66	2.25
Employment L	100	98.8	100	98.0
Normalized output $\hat{Y}$	100	98.1	100	96.9
Normalized average productivity $\hat{Y}/L$	100	99.3	100	98.9
Number of active products N	0.964	0.958	0.964	0.957
Job-creation rate (%)	17.0	4.7	17.0	7.5
Job-creation rate from entry (%)	6.4	4.3	6.4	4.3
Job-destruction rate (%)	17.0	4.7	17.0	7.5
Job-destruction rate from exit (%)	2.8	2.4	2.8	2.3
R&D ratio R/Y (%)	11.5	10.6	11.5	10.4

Note: L, $\hat{Y}$, and $\hat{Y}/L$ are set at 100 in the $\tau = 0.0$ case.

inate the effects of the higher persistence. In particular, in the new calibration, the firms more frequently face situations in which a large downsizing is necessary. Overall, the negative growth effect is only slightly stronger with this specification than in section III.

Extension 2: Small entrants and heterogeneous growth. — A shortcoming of the baseline model is that it generates entrants that are larger than incumbents, which is not consistent with US data. Also, existing empirical evidence suggests Gibrat's law does not hold for small firms; small firms grow faster than large firms (e.g., Evans, 1987; Hall, 1987). In this section, we modify the assumptions on the entry process and on the innovation of incumbents while maintaining the assumption that α is i.i.d. We find the main results of the paper are robust to these modifications that improve the fit of the model.

We first assume entrants are more likely to innovate over lower-quality products. This assumption is likely to be more reasonable than the assumption of random innovation, considering that innovations tend to be cumulative (e.g., Aghion et al., 2001; Mukoyama, 2003), and improving upon a very advanced product is difficult. Second, we also assume the firms with lower (relative) quality have a lower innovation cost. Previous literature on R&D and innovation emphasizes positive spillovers across firms, and a lower-quality product is more likely to benefit from these spillovers. These assumptions help the model match several empirical regularities that the baseline model is not able to match. First, because entrants tend to innovate over low-quality products, entrants tend to be less productive and therefore smaller than in the baseline model. Second, because lower-quality firms, which are small, innovate more frequently, small (and young) firms tend to grow faster, thus allowing the model to deviate from Gibrat's law.

More specifically, we first make the probability that an incumbent is taken over by an entrant dependent 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 $u(\hat{q})$ 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 also assume $\omega'(\hat{q}) \leq 0$. 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 more difficult to imitate. This assumption 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 on 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 in 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's, 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.[47]

To compute the model, we must specify both the weight function and the

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

innovation cost function. We assume the weight function takes the form

$$\omega(\hat{q}) = 1 + \chi_1 e^{-\chi_2 \hat{q}}, \tag{13}$$

where $\chi_1 \geq 0$ and $\chi_2 \geq 0$. The parameter χ_1 controls the relative displacement probability of high- and low-productivity firms, whereas χ_2 controls the slope of the decline in the displacement probability.[48]

The innovation cost is assumed to take the form

$$\theta_I(\hat{q}) = \bar{\theta}_I(1 - (1 - \chi_3)e^{-\chi_4 \hat{q}}), \tag{14}$$

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.[49] 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 (13) and χ_3 and χ_4 in equation (14)), are presented in Appendix E. As shown in Appendix E, this model better fits the data in terms of the firm size distribution.

Table 7—: Smaller entrants and the deviation from Gibrat's law

	Section III		Extension	
	$\tau = 0.0$	$\tau = 0.3$	$\tau = 0.0$	$\tau = 0.3$
Growth rate of output g (%)	1.48	1.39	1.48	1.39
Average innovation probability by incumbents $\bar{x}_I$	0.084	0.091	0.213	0.237
Innovation probability by entrants x_E	0.143	0.143	0.079	0.079
Creative-destruction rate μ (%)	2.65	2.30	5.17	4.25
Employment L	100	98.8	100	98.4
Normalized output $\hat{Y}$	100	98.1	100	96.6
Normalized average productivity $\hat{Y}/L$	100	99.3	100	98.2
Number of active products N	0.964	0.958	0.773	0.735
Job-creation rate (%)	17.0	4.7	17.5	5.3
Job-creation rate from entry (%)	6.4	4.3	6.7	4.3
Job-destruction rate (%)	17.0	4.7	17.5	5.3
Job-destruction rate from exit (%)	2.8	2.4	4.3	3.7
R&D ratio R/Y (%)	11.5	10.6	11.9	10.9

Note: Note: L, $\hat{Y}$, and $\hat{Y}/L$ are set at 100 in the $\tau = 0.0$ case. The first two columns report the results of the entrant-driven growth calibration.

As in section III, we consider an experiment of setting $\tau = 0.3$. Table 7 shows the results.[50] The section III results are also presented for the purpose of comparison. The qualitative results are identical to those obtained with the model in

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

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

[50]The job-creation rate by entry is still larger than the entry rate in the extended model, indicating that the size of entrants is still larger than the size of incumbents. However, compared to section III, the relative size of entrants is substantially smaller. With our functional forms, this value turns out to be the lower bound of the entrants' size in the parameterizations that we can compute.

section III (in the entrant-driven growth case). In particular, the firing tax leads to opposite response of the incumbents' and the entrants' innovation. The incumbents' innovation increases, and the entrants' innovation decreases; the overall effect on growth is negative.

This extended model contains an additional 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 effect 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 not to matter quantitatively. The results of the previous section are robust to the modifications that bring the model outcome closer to the data.

B. *Discussions*

Here we discuss the robustness of our quantitative results to other model specifications. We also discuss the results of the empirical effects of firing costs on growth. A large part of the analysis is relegated to the Appendix.

THE SOURCES OF INNOVATION. — We find that firing costs can affect the innovation of entrants and incumbents in opposite directions. The overall effect on the aggregate economy therefore depends on the details of the innovation process of entrants and incumbents. We investigate below the extent to which different specifications and calibration strategies can generate results that differ from our results (presented in section III).

Innovation size. We first consider an alternative calibration strategy in which the innovation size is smaller for both entrants and incumbents. We set λ_I to match the relative proportion of establishments creating jobs and destroying jobs, and keep the relative innovativeness of entrants the same as in the entrant-driven growth case in section III. We consider two different methods of keeping "relative innovativeness" the same as in section III: the first is to keep $\lambda_E/\lambda_I = 6$, and the second is to keep $(1 + \lambda_E)/(1 + \lambda_I) = 2$. The results are reported in Appendix E.3.

In the calibration with $\lambda_E/\lambda_I = 6$, 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 from the smaller contribution of entrants to the growth rate. Although λ_E/λ_I is the same as in section III, the contribution of entrants to the growth rate is lower. The decline in the entry rate therefore has a smaller impact on aggregate productivity growth. In the calibration with $(1 + \lambda_E)/(1 + \lambda_I) = 2$, the contribution of entrants to the growth rate is closer to the contribution in section III, and we find the growth effect is also closer to the effect in section III. This finding indicates that, in the current setting, the relevant statistics for the contribution of entrants to growth and for the overall effect of firing costs on growth is $(1 + \lambda_E)/(1 + \lambda_I)$ rather than λ_E/λ_I.

Only entrants innovate. We consider the extreme case in which only entrants innovate. The results are reported in Appendix E.3. We find the firing tax leads to a larger decline in innovation and aggregate productivity growth than in section III. Furthermore, because the positive impact on the incumbents' innovation is absent, the firing tax unambiguously reduces the growth rate. This result illustrates the importance of including the incumbents' innovation in the analysis. As our baseline model shows, accounting for the incumbents' innovation can overturn this result when incumbents are the main driver of growth. At the very least, ignoring the innovation by incumbents would have led us to overestimate the negative consequences of the firing tax on growth.

Other margins of innovation. In our model, innovation leads to improvements in product quality. Another possible margin of innovation to consider is the creation of new varieties. To complement the analysis, we build a separate model with expanding varieties à la Romer (1990) and compute the effect of firing taxes in that setting. Appendix E.5 contains a full description of the model and the results. The firing tax reduces profitability and hence lowers the creation of new products. We show the growth rate decreases with the firing tax. The mechanism is similar to the one behind the lower entry rate in our baseline model.[51]

Another type of innovation that we do not consider in this paper is the creative destruction by incumbents, whereby incumbent firms can come up with a better-quality version of products that are already produced by other firms. The drivers of the incumbents' creative destruction are very similar to the drivers of the entrants' innovation in our model. In fact, if such innovations result in the creation of new establishments, our analysis already includes this type of innovation in the entry component, because the labor market statistics used to calibrate the model are computed at the establishment level. One caveat of this interpretation is that we do not account for the possibility that firms can move workers from one establishment to another. In fact, the tax-escaping effect can work *across* establishments—firms may want to open another establishment to avoid firing taxes. In this case, the effect of the firing tax on incumbents' creative-destruction innovation may qualitatively differ from the baseline model because the tax-escaping effect encourages the incumbents' creative-destruction. Similarly, the creation of new(-to-the-market) varieties by incumbents can be captured

[51] Bertola (1994) analyzes a model similar to our Appendix E.5. He analytically shows the growth rate is decreasing in firing costs in a setting where firm's productivity takes one of two values.

in the model by the creation of new varieties by entrants discussed above. Here again, the same caveat applies.

Comparison with labor taxes and R&D subsidies. — The effects of tax and transfer policies in the labor market have been extensively studied. Because the firing tax and the standard labor tax both generate distortions in the labor market, comparing the two policies will give us additional insights into the specific effects of the firing tax. In addition, comparing the effect of a labor tax in our model with the results of the literature allows us to check the validity of our model.

We introduce to the baseline model a tax rate $\eta \in [0, 1]$ on labor. The budget constraint for the consumer changes to

$$A_{t+1} + C_t = (1 + r_t)A_t + (1 - \eta)w_t L_t + T_t.$$

To facilitate the comparison with the literature, we consider a more general form of period utility function

$$\log(C_t) - \xi \frac{L_t^{1+\nu}}{1+\nu},$$

where $\nu \geq 0$. Note that $\nu = 0$ corresponds to our baseline model.[52] We report the outcomes of a 5% labor tax (i.e., $\eta = 0.05$), in the entrant-driven growth case, for different values of ν in Appendix E.4. In the baseline model ($\nu = 0$), we find that a 5% labor tax reduces the growth rate to 1.38%, whereas the firing tax reduces the growth rate to 1.39%.[53] The growth effect of the 30% firing tax is therefore of the same magnitude as that of a 5% labor tax.

Another method of assessing the quantitative impact of the firing tax is to compute the R&D subsidy that would be needed to offset the negative impact of the firing tax on growth. The R&D subsidy changes the innovation cost for incumbents to

$$\mathbf{r}_{Ijt} = (1 - s)\theta_I Q_t \frac{q_{jt}}{\bar{q}_t} {x_{Ijt}}^{\gamma}$$

and the innovation cost for entrants to

$$\mathbf{r}_{Ejt} = (1 - s)\theta_E Q_t {x_{Ejt}}^{\gamma}.$$

We find that to cancel out the growth effect of the 30% firing tax, we need to introduce a 7.3% innovation subsidy ($s = 0.073$).

[52] Ohanian, Raffo and Rogerson (2008) use a similar utility function and show the model can fit the patterns of labor supply in postwar OECD countries once the changes in taxes are taken into account. Rogerson and Wallenius (2009) consider this form of utility function in a richer model of life cycle labor supply. See Appendix E.4 for details.

[53] We have also made comparisons to Rogerson and Wallenius (2009) results by recalibrating the model to $\eta = 0.30$ and running an experiment in which we change the tax to $\eta = 0.50$. See Appendix E.4 for details.

Empirical analysis of the effect of firing costs on growth. — As detailed in section III.B, the overall effect of firing costs on growth is the result of two opposing effects: firing costs may increase the incumbents' innovation, whereas they reduce the entrants' innovation. In principle, the overall effect can be positive or negative, depending on which of these two effects dominate.

To gain further insights into this question, we analyze empirically the effects of firing costs on innovation spending. Several studies have investigated the consequences of firing costs for job reallocation (Micco and Pagés, 2007; Haltiwanger, Scarpetta and Schweiger, 2014; Davis and Haltiwanger, 2014), but only a few studies focus on aggregate productivity (Autor, Kerr and Kugler, 2007; Bassanini, Nunziata and Venn, 2009; Acharya, Baghai and Subramanian, 2013; Ueda and Claessens, 2016). To complement these existing studies, we first evaluate whether a relationship exists between industry-level R&D spending and the strictness of employment-protection regulation. Then, we go beyond the variation across countries and over time, and we exploit the variation across industries as well. Similarly to Bassanini, Nunziata and Venn (2009), we test whether stricter employment protection regulations tend to reduce R&D spending more in industries in which dismissal regulations are more likely to be binding. We use the industry layoff rate in the US as a measure of how binding the employment regulation is in each industry. The empirical results are reported in Appendix F. We find that countries with stricter employer protection tend to have lower R&D spending. Employment protection regulation, however, does not have a systematically larger effect in industries with a higher layoff rate. From the viewpoint of our theoretical model, the positive and negative effects of employment protection on R&D may offset each other to produce mixed results.

V. 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 influences not only the *level* but also the *growth* rate of aggregate productivity. The model that we propose is flexible and can easily accommodate various extensions. We believe our model will be useful for future studies of how other barriers to reallocation affect aggregate productivity growth.

We examine a particular type of barrier: firing costs. We find firing costs can have opposite effects on entrants' innovation and incumbents' innovation. Firing costs reduce entrants' innovation whereas they may enhance incumbents' innovation. As a result, firing costs change the composition of innovation, and to the extent that the effect on incumbents and the effect on entrants do not offset each other, they also affect aggregate innovation. Our quantitative results show the overall effect on growth is negative when entrants' innovation is the main driver of growth. In the alternative calibration in which incumbents' innovation is the main driver of growth, firing taxes can enhance aggregate productivity growth. Our results also suggest the welfare effect coming from the growth channel can be significant.

Although the focus of this paper is theoretical, the opposing effects on entrants and incumbents call for an empirical analysis of the consequences of firing costs on growth. The existing literature on the topic has obtained mixed results. To complement existing work, we have run several regressions using cross-country data on industry-level R&D spending. We find that although stricter employment protection regulation is associated with lower industry-level R&D spending, R&D spending is not systematically lower for industries that are more likely to be constrained by the regulation. Although the mixed results are not surprising in light of the opposing forces unveiled by our model, we believe further empirical investigations on the effects of firing costs on innovation are needed.

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