Lack of Selection and Limits to Delegation: Firm Dynamics in Developing Countries*

Ufuk Akcigit
University of Chicago, NBER, CEPR

Harun Alp
University of Pennsylvania

Michael Peters
Yale University and NBER

April 14, 2017

Abstract

Firm dynamics in developing countries show striking differences to those in developed countries. While some firms do grow as they age, most firms are simply stagnant and do not exit despite being small. We ask to what extent these patterns could be driven by cross-country differences in the efficiency of managerial delegation. If delegating managerial tasks is difficult in poor countries, entrepreneurs with growth potential might decide to remain small, as they have to rely on their own scarce time to run their daily operations. This in turn reduces competition, slows down firm selection through *creative destruction*, and hence keeps subsistence firms with little growth potential in the market. To quantify the importance of this mechanism, we construct a model of firm growth and calibrate it to firm-level data from the U.S. and India. Three results emerge: (i) The Indian economy suffers from a lack of selection, whereby a low rate of creative destruction allows subsistence producers to survive. (ii) The high delegation efficiency in the U.S. is an important determinant of why U.S. firms are large. (iii) While managerial delegation is inefficient in India, its effect on the lifecycle of Indian firms is limited due to important complementarities between the delegation efficiency and other factors affecting firm growth.

Keywords: Economic development, growth, selection, competition, firm dynamics, management, entrepreneurship, creative destruction.

JEL Classifications: O31, O38, O40

*We thank the seminar and conference participants at Harvard, MIT, University of Chicago, Stanford, Princeton, Yale, USC, LSE, the Productivity, Development & Entrepreneurship, and Macroeconomics Within and Across Borders Meetings at the NBER Summer Institute, the NBER Development Program and EFG Meeting, Stanford CID/IGC Conference, AEA Meetings, OECD/NBER Conference on Productivity and Innovation, Minnesota Macro, NYU, Penn State, Einaudi, University of Houston, Barcelona GSE Summer Forum, Kauffman Entrepreneurship Conference, London Macroeconomics Conference, CAED 2015 Conference, Cologne Workshop on Macroeconomics, SKEMA Growth Conference, UPenn Growth Reading Group, and UPenn Macro Lunch for helpful comments. In particular we would like to thank our discussants Francesco Caselli, John Haltiwanger, Chang-Tai Hsieh, Rasmus Lentz, and Yongs Shin. We furthermore received very valuable feedback from Abhijit Banerjee, Nick Bloom, Matthew Cook, Jeremy Greenwood, Pete Klenow, Chad Jones, Sam Kortum, Robert E. Lucas, Giuseppe Moscarini, Luis Serven, Andrei Shleifer, and Nancy Stokey. Chang-Tai Hsieh and Pete Klenow have kindly shared some of their data with us. Jeremy Pearce provided excellent research assistance. Akcigit gratefully acknowledges financial support from the World Bank, the Alfred P. Sloan Foundation, the Ewing Marion Kauffman Foundation, and the National Science Foundation.

1 Introduction

The process of firm dynamics differs vastly across countries. While firms in rich countries experience rapid growth conditional on survival, firms in poor countries remain small and do not grow as they age. Hsieh and Klenow (2014), for example, show that the average firm in the U.S. has grown by a factor of four by the time it is 30 years old. In contrast, firms in India see very little growth as they age, making 30-year-old firms barely bigger than new entrants.[1] A salient regularity underlying these aggregate numbers is the plethora of tiny producers in developing economies that are entirely stagnant. A case in point is the Indian manufacturing sector, where 77% of the entering firms have at most two workers. More strikingly, this stock of micro-firms is essentially independent of age, i.e., these firms also do not exit despite staying small. This is very different in developed economies like the U.S., which are characterized by a pronounced "up-or-out" phenomenon, where firms also enter small but then either exit or expand.

In this paper we ask to what extent cross-country differences in the ease of managerial delegation can quantitatively explain these patterns. We focus on the importance of managers for both theoretical and empirical reasons. At a conceptual level we think that frictions in managerial delegation are a very natural mechanism for why the returns to growing large might be small in poor countries. If workers require managerial oversight but the entrepreneur's time to provide such services herself is limited, firms need to delegate as they grow. If there are serious frictions to delegation in poor countries, firms might optimally decide not to hire outside managers and remain small. Additionally, there is recent direct empirical evidence that the efficiency of managerial delegation varies systematically across countries [see e.g., Bloom and Van Reenen (2007, 2010)] and that firms in India are constrained in their managerial resources: Bloom et al. (2013), for example, find that the delegation of decision rights hardly extends to managers outside the family and that the number of male family members is the dominant predictor of firm size.

We formalize this intuition by introducing the need for managerial delegation in a firm-based Schumpeterian model of endogenous growth in the spirit of Klette and Kortum (2004). In the model, firm growth occurs via creative destruction, i.e., firms grow at the expense of other producers, and the incentives to expand depend on the prevailing delegation environment. To take seriously the idea that some firms might simply not be destined to grow, we explicitly allow for heterogeneity in firms' growth potential. In particular, we follow a recent empirical literature, which argues that some entrepreneurs are *transformative* i.e., they have the necessary skills to expand, while others are *subsistence* entrepreneurs, which might simply lack the ability to grow their firms beyond a certain size (Schoar, 2010; Decker et al., 2014). Because such firms only survive as long as they are not driven out of the market, the degree of selection, i.e., the extent to which such stagnant firms manage to survive, is endogenously determined by the transformative entrepreneurs' incentives to expand.

[1] Strictly speaking, this evidence stems from the analysis of plant-level (instead of firm-level) data. While we will refer to producers as firms in the theory, we will look at both firm- and plant-level data in our quantitative analysis.

In our model, firms' expansion incentives, besides other factors as described below, respond to the underlying delegation environment: if the entrepreneur's own managerial input is a fixed factor, production features decreasing returns and marginal profits decrease in firm size. This reduces firms' incentives to grow large. Entrepreneurs can overcome such declining marginal returns by delegating decision power to outside managers as their firms expand. If, however, the economy's delegation efficiency is low (for instance due to imperfect contractual enforcement or lack of trust), transformative entrepreneurs have little incentive to grow as they anticipate not being able to delegate decision power effectively. Improvements in delegation efficiency therefore raise the returns to growing large, induce more selection whereby stagnant firms are wiped out quickly, make the life-cycle of incumbent firms steeper, and reduce the aggregate importance of small firms in the economy.

To analyze the quantitative importance of this delegation mechanism, we consider the key structural parameters to be country specific and calibrate them to micro data from the U.S. and India independently. This is important for two reasons. First, we are interested in the various country-specific determinants of firm dynamics and our calibration strategy allows us to analyze these underlying alternative reasons separately. Second, allowing both countries to differ in various alternative margins prevents us from loading all the differences on a single mechanism and hence allows us to credibly quantify the direct effect of delegation efficiency differences between the U.S. and India. This is highlighted by our treatment of the share of managerial employment, which is a key moment to identify differences in delegation efficiency between the U.S. and India. Because the managerial employment share is an equilibrium object, it is correlated with factors other than delegation efficiency. In our setup, the equilibrium amount of managerial hiring is allowed to depend explicitly on three ingredients:

1. *Managerial Human Capital:* The extent of managerial hiring can depend on the supply of managerial human capital. If managerial skills are relatively abundant in one country, everything else equal, the equilibrium share of managers in the workforce would be higher.

2. *Firm Growth due to Non-managerial Factors:* Because firm size and managerial hiring are complements, countries with larger firms will have more managerial employment in equilibrium. Hence, if firms are bigger because of non-managerial factors, they demand more managers. For instance, if the share of subsistence entrepreneurs or the costs of expansion are lower (due to more efficient capital markets or less distortionary regulation, lower payroll taxes, better infrastructure, or even cultural differences), firms would grow more and demand more managers, on average.

3. *Delegation Efficiency:* Firms' incentives to delegate can depend on the delegation efficiency. If delegation is easier (e.g., due to a stronger rule of law or higher trust in non-family managers), entrepreneurs are more likely to delegate managerial tasks to outside managers.

To distinguish these three channels and, in particular, to identify the importance of delegation efficiency, we rely on different sources of information. First, we use plant-level information from the manufacturing sector in the U.S. and India to measure plants' life-cycle growth and entry and exit patterns. These moments are particularly informative to discipline the initial importance of subsistence entrepreneurs and other, non-managerial determinants of firm growth (i.e., item #2 in the above list). Second, we rely on data about managerial employment patterns and managerial wages from the U.S. and the Indian Census, to calibrate differences in the delegation efficiency and managerial human capital between these two countries. Empirically, outside managers account for only 1.7% of the labor force in India. In the U.S., this number amounts to 12.4%. Finally, to distinguish the effect of delegation efficiency (item #3 above) and managerial human capital (item #1 above) in accounting for this higher importance of outside managers in the U.S., we exploit information on pre- and post-migration outcomes of Indian immigrants to the U.S., taking into account also the selection among immigrants from India. We then use the calibrated model to quantify the extent to which cross-country differences in the delegation environment can explain the variation in the implied processes of firm dynamics.

Our analysis yields three main conclusions. First, we find that the Indian economy suffers from a significant lack of selection, whereby subsistence producers with little growth potential survive for a long time. While this is partly due to a high initial share of subsistence firms at the time of entry, we show that the main culprit of this lack of selection is the low rate of creative destruction, which allows even small firms to survive. We believe that this result is important because it provides a somewhat different way to think about firms in developing countries. In our economy a large number of small firms is *not* a reflection of frictions that those small firms face, but rather an indication of a lack of competition coming from larger firms, which helps subsistence producers survive. In particular, the glut of small firms in poor countries is a symptom of frictions that *bigger* firms face. This implies that policies aimed at supporting small firms, e.g., micro-finance programs, while potentially desirable for their redistributive properties, could be harmful to the economy by reducing the reallocation of resources from small stagnant firms to large expanding firms. This is consistent with the dual economic view of development by La Porta and Shleifer (2008, 2014), who argue that the decline in informality associated with economic growth "is the result of a replacement of inefficient informal firms by efficient formal ones" (La Porta and Shleifer, 2014, p. 121).

Second, the cross-country variation in delegation efficiency is quantitatively important to account for differences in the process of firm dynamics. According to our estimates, both the delegation efficiency and the average managerial human capital (relative to production workers) are approximately twice as high in the U.S. compared to India. Quantitatively, these differences imply that if firms in the U.S. were facing the same delegation efficiency as firms in India, the observed gap in life-cycle growth between Indian and U.S. firms would be roughly 25% lower.

Finally, there are important complementarities between the returns to delegation and other differences between the U.S. and India. While a decline in delegation efficiency in the U.S. reduces firm growth substantially, the Indian counterpart is less pronounced: If Indian firms were able to hire managers as seamlessly as firms in the U.S., the implications for the resulting life-cycle are much more modest. The reason is that in addition to the aforementioned delegation frictions, other non-managerial factors that determine firm expansion are also less efficient in India. Hence, other frictions, such as credit market imperfections or distortions to market entry not only hamper firm growth directly, but also reduce the effect of improvements in the delegation environment on firms' expansion incentives.

Related Literature That managerial delegation might be a key aspect to firm dynamics goes back to the early work of Penrose (1959), who argues not only that managerial resources are essential for firms to expand but that this scarcity of managerial inputs prevents the weeding out of small firms as "the bigger firms have not got around to mopping them up" (Penrose, 1959, p. 221). Recently, empirical evidence for this managerial margin has accumulated. Using data across countries, there is evidence that managerial practices differ across countries (Bloom and Van Reenen, 2007, 2010), that firms in developed countries are both larger and delegate more managerial tasks to outside (non-family) managers (Fukuyama, 1996; La Porta et al., 1997; Bloom et al., 2012) and that both human capital and contractual imperfections are important in explaining the lack of managerial delegation in poor countries (Laeven and Woodruff, 2007; Bloom et al., 2009). The importance of managerial and entrepreneurial human capital for economic development is also stressed in the empirical work by Gennaioli et al. (2013).

We formalize and quantify the macroeconomic importance of such managerial considerations by providing a new theory of firm dynamics and the resulting firm size distribution in developing countries.[2] While many recent papers have attempted to measure and explain the static differences in allocative efficiency across firms [e.g., Restuccia and Rogerson (2008), Hsieh and Klenow (2009), and more recently Gopinath et al. (2017), among many others[3]] there has been less theoretical work explaining why firm dynamics differ so much across countries. A notable exception is the work by Cole et al. (2016), who argue that cross-country differences in the financial system affect the type of technologies that can be implemented. Like them, we let the productivity process take center stage. However, we turn to the recent generation of micro-founded models of Schumpeterian growth, following Klette and Kortum (2004), who have been shown to provide a tractable and empirically successful theory of firm dynamics [see for instance, Acemoglu et al. (2013); Akcigit and Kerr (2017); Garcia-Macia et al. (2015); Lentz and Mortensen (2005, 2008)].[4]

[2] An overview of some regularities of the firm size distributions in India, Indonesia, and Mexico is contained in Hsieh and Olken (2014).

[3] As far as theories are concerned, there is now a sizable literature on credit market frictions (Buera et al., 2011; Moll, 2014; Midrigan and Xu, 2014), size-dependent policies (Guner et al., 2008), monopolistic market power (Peters, 2016) and adjustment costs (Collard-Wexler et al., 2011). A synthesis of the literature is also contained in Hopenhayn (2012) and Jones (2013).

[4] As in Aghion and Howitt (1992), firm dynamics are determined through creative destruction, whereby successful firms expand through replacing other producers. See Aghion et al. (2014) for a survey of the Schumpeterian growth literature.

Importantly, we explicitly allow for heterogeneity in firms' growth potential. This heterogeneity is not only at the heart of our mechanism, but also empirically required to match the micro-data. There is ample empirical evidence for the importance of such heterogeneity. Besides the contributions of Schoar (2010) and Decker et al. (2014) cited above, Hurst and Pugsley (2012), for example, show that there are heterogeneous types of entrepreneurs in the U.S. economy, a majority of whom intentionally choose to remain small. In the context of developing countries, Banerjee et al. (2015) present experimental evidence on persistent differences in growth potential. Similar findings are also reported in De Mel et al. (2008). Complementary, there is also a recent literature that argues that models without such heterogeneity in growth potential are unable to explain the very-rapid growth of a subset of the U.S. firms [see e.g., Luttmer (2011), Acemoglu et al. (2013), or Lentz and Mortensen (2016)]. Recently, Gabaix et al. (2016) generalized this logic to the debate on inequality.

We focus on inefficiencies in the interaction between outside managers and owners of firms to explain differences in firms' demand for expansion. Caselli and Gennaioli (2013) also stress the negative consequences of inefficient management, but focus on static misallocation. We, in contrast, argue that managerial frictions within the firm reduce growth incentives and hence prevent competition from taking place sufficiently quickly on product markets. Powell (2012), Bertrand and Schoar (2006), and Grobvosek (2015) study within-firm considerations where firms ("owners") need to hire managers subject to contractual frictions. In contrast to our theory, all these papers assume that firm productivity is constant, i.e., there is no interaction between the delegation environment and firms' endogenous growth incentives. Guner et al. (2015) and Roys and Seshadri (2014) present recent dynamic models of (managerial) human capital accumulation and economic development. In contrast to us, they do not focus on the implications of creative destruction for the resulting process of selection and firm dynamics. Finally, there is a large literature on management and the hierarchical structure of the internal organization of the firm; see Garicano and Rossi-Hansberg (2015) for a survey. This literature has a much richer microstructure of firms' delegation environment, but does not focus on the resulting properties of firm dynamics.

The remainder of the paper is organized as follows. In Section 2, we describe the theoretical model, where we explicitly derive the interaction between firms' delegation decisions and their incentives to grow. Section 3 summarizes the data that we use in our quantitative analysis and provides some basic correlations from the Indian micro-data in relation to the theoretical framework. In Section 4, we calibrate the model to the U.S. and Indian-micro data and provide our main analysis to study the importance of delegation environment on firm dynamics. Section 5 provides various robustness checks of the main quantitative results. Section 6 concludes. All proofs and additional details are contained in the Appendix. The Online Appendix contains further results.

2 Theory

We consider a continuous time economy, where a representative household maximizes the sum of per period utilities $U(C_t) = \ln(C_t)$ and discounts the future at rate ρ. Household optimization delivers the usual Euler equation where the interest rate r_t is equal to the sum of the discount rate ρ and the growth rate of consumption of the final good, which we take as the numeraire:

$$r_t = \rho + g_t. \tag{1}$$

The final good Y_t is used for consumption C_t and investment in productivity growth by incumbents R_t and entrants $R_{E,t}$. Therefore the resource constraint is simply

$$Y_t = C_t + R_t + R_{E,t}. \tag{2}$$

To save on notation we will drop the time subscript t whenever it does not cause any confusion.

2.1 Technology

The final good is a Cobb-Douglas composite of a measure one of intermediate varieties:

$$\ln Y = \int_0^1 \ln y_j dj, \tag{3}$$

where y_j denotes the amount of variety j. A firm is a collection of varieties as we explain below. The production of intermediate goods is conducted by heterogeneous firms and requires both production workers and managers. In particular, firm f can produce good j according to

$$y_{jf} = q_{jf} \mu \left(e_{jf}\right) l_{jf}, \tag{4}$$

where q_{jf} is the firm-product specific efficiency, l_{jf} is the number of production workers employed for producing intermediate good j, e_{jf} denotes the amount of managerial services firm f allocates toward the production of good j, and $\mu\left(e_{jf}\right) \geq 1$ is an increasing function translating managerial services into productivity units. As in Klette and Kortum (2004), firm productivity in each variety q_{jf} is endogenous and the result of past innovation decisions. Also, note that the technology in (4) implies that the labor cost of producing one unit y_{jf} is given by $MC_j = w_P / q_{jf} \mu(e_{jf})$, where w_P is the equilibrium wage for production workers.

Because firms' outputs within product variety j are perfect substitutes, in equilibrium each variety j is produced by a single firm f, which has the highest productivity q_{jf}. We will therefore refer to this firm as the producer of product j and denote the producer's productivity for variety j by q_j. Note that a given firm can produce multiple varieties if it was successful in innovating in the past and hence has the highest efficiency in multiple markets.

In order to focus on the interaction between managerial delegation and the resulting equilibrium process of firm *dynamics*, we keep the *static* market structure as tractable as possible. To do so, we assume that in each market j there is a competitive fringe of potential producers that can produce variety j at marginal costs w_P/q_j.[5] Because the market leader faces a demand function with unitary elasticity it will engage in limit pricing, i.e., set its price equal to the marginal costs of the competitive fringe. The gross profits after paying for production workers l_j (but before paying for the managers) are therefore given by

$$\pi_j(e) = [p_j - MC_j]y_j = \left[\frac{\mu(e) - 1}{\mu(e)}\right] Y. \tag{5}$$

Expression (5) stresses that firm f's profits on variety j depend only on the amount of managerial services that it allocates toward the production of the jth variety. Because managerial inputs increase physical productivity, more managerial inputs allow firms to increase their profitability.

For analytical convenience, we assume that $\mu(e) = \frac{1}{1-e^{\sigma}}$, where $e \in [0, 1)$ and $\sigma < 1$. This implies that firm f's profit in variety j is given by

$$\pi(e_j) = e_j^{\sigma} Y, \tag{6}$$

i.e., profits are a simple power function of managerial effort parameterized by the elasticity σ. Note that if the producing firm has no managerial services at its disposal, it is unable to outcompete the competitive fringe and hence earns no profits.

2.2 Delegation and the Market for Outside Managers

Managerial services e can be provided both internally by the entrepreneur herself, and by outside managers. Suppose that each entrepreneur has a fixed endowment of T managerial efficiency units, which she provides inelastically to her firm. If an entrepreneur is the current producer in n markets and decides to run her firm alone, then she will have $e_j = T/n$ units of managerial services per variety.[6] Equation (6) then implies that the total profit of the firm is simply

$$\Pi^{self}(n) = \sum_{j=1}^{n} \pi(e_j) = n \times \pi\left(\frac{T}{n}\right) = T^{\sigma} n^{1-\sigma} Y.$$

This expression has a simple but important implication: While the profits of the firm are increasing in the number of varieties n, they do so at a decreasing rate. The reason is that the owner has a fixed time endowment T and hence runs into span of control problem as in Lucas (1978). This concavity of $\Pi^{self}(n)$ has important *dynamic* implications: as marginal returns are decreasing in

[5] This assumption allows us to abstract from strategic pricing decisions of firms who compete with firms of different productivity. A related model with strategic pricing behavior is analyzed in Peters (2016). In terms of primitives, the fringe firms have access to the same technology as the leading firm and to a level of managerial services μ^{fringe}, which we normalize to unity.

[6] That she will want to spread her T units of managerial time equally across all product lines follows directly from the concavity of π in (6).

n, the incentives to grow and to break into new markets *decline* as the size of the firm increases. To prevent this scarcity of managerial inputs from being a drag on growth incentives, the entrepreneur can decide to bring outside managers into the firm. It is this process that we refer to as *delegation*.

Delegation and the Demand for Outside Managers Managerial efficiency units can be hired on a spot market at wage rate w_M. In particular, suppose that the productivity of outside managers' human capital is given by ξ, i.e., if an owner of a firm with n varieties hires m_j units of managerial human capital for the production of variety j, the total amount of managerial services e_j is given by

$$e_j = T/n + \xi \times m_j. \tag{7}$$

The parameter ξ, which we refer to as the *delegation efficiency*, is a key parameter for our analysis. In particular, we think of ξ as being country-specific and dependent on various fundamentals. First, ξ could depend on the *contractual environment*. If contractual imperfections are severe, entrepreneurs might need to spend substantial amounts of their own time monitoring their managerial personnel. This reduces the net time gain each outside manager adds to the firm. Second, ξ could depend on the level of *technology* available to the firm. If managerial efficiency is complementary with IT equipment, for example, technological differences across countries will be a source of variation in ξ. Third, ξ could capture cultural factors like *trust* or social norms, which facilitate the delegation of decision power. Finally, ξ might depend on the level of *financial development*, since more developed financial markets might give the entrepreneur the opportunity to incentivize her managers better. In this paper we are agnostic about the exact determinants of ξ.[7] We will rather take it as a country-specific parameter, calibrate it directly within our model, and then quantify the extent to which cross-country differences in ξ can account for the differences in firm-dynamics.

Because managers and workers are hired on a spot market, the delegation problem is static and the owner simply maximizes the total profits of the firm by choosing the optimal amount of managerial inputs. Using (6) and (7), total profits of a firm who is producing n varieties are therefore given by

$$\Pi(n) \equiv \sum_{j=1}^{n} \max_{m_j \geq 0} \left\{ \left(\frac{T}{n} + \xi m_j \right)^{\sigma} Y - w_M m_j \right\}, \tag{8}$$

where w_M is the managerial wage.

The maximization problem in (8) defines both firms' demand for managerial inputs and their final profit function. Two properties are noteworthy. First of all, the entrepreneur's inelastically supplied managerial input T generates a well-defined extensive margin for managerial hiring. In

[7] However, in Section (OA-1.2) in the Online Appendix, we provide a simple micro-founded example, where a contractual game between the owner and outside managers leads to equation (7) and ξ is a combination of explicit structural parameters.

particular, define the endogenous *delegation cutoff* $n^*(\xi)$ as

$$n^*(\xi) = T \times \left(\frac{\omega_M}{\sigma\xi}\right)^{\frac{1}{1-\sigma}}, \tag{9}$$

where $\omega_M = w_M/Y$ is the normalized managerial wage. All firms with $n < n^*(\xi)$ do not hire any outside managers but solely rely on the entrepreneurs' own managerial time. Intuitively, for small firms, the amount of internal managerial time per variety, T/n, is large so that the marginal product of outside managers is small. Note that the cutoff n^* is decreasing in ξ and increasing in ω_M. Hence, the more efficient outside managers are, the more likely is it that even small firms utilize outside managers. Conversely, if managers are expensive (relative to the size of the market Y), the critical size at which firms start to delegate increases.

Secondly, it is easy to verify that the optimal managerial demand $m(n)$ is the same for each variety the firm produces and is given by

$$m(n) = \begin{cases} 0 & \text{if} \quad n < n^*(\xi) \\ \left(\frac{\sigma}{\omega_M}\right)^{\frac{1}{1-\sigma}} \xi^{\frac{\sigma}{1-\sigma}} - \frac{1}{\xi}\frac{T}{n} & \text{if} \quad n \geq n^*(\xi) \end{cases}. \tag{10}$$

This expression implies that similar comparative statics hold true for the intensive margin of delegation: the optimal amount of managerial human capital per variety stemming from outside managers is increasing in ξ and n and decreasing in ω_M.

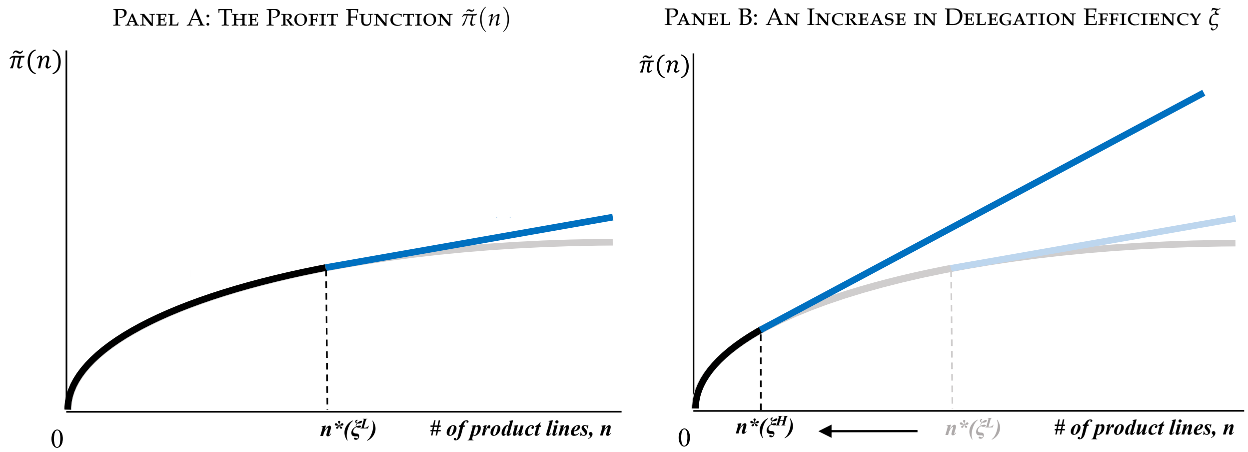
Substituting firms' optimal delegation policies (9) and (10) into (8) implies the following endogenous profit function:

$$\Pi(n) = \tilde{\pi}(n) \times Y \quad \text{where} \quad \tilde{\pi}(n) = \begin{cases} T^{\sigma} \times n^{1-\sigma} & \text{if} \quad n < n^*(\xi) \\ T\frac{\omega_M}{\xi} + (1-\sigma)\left(\frac{\sigma\xi}{\omega_M}\right)^{\frac{\sigma}{1-\sigma}} \times n & \text{if} \quad n \geq n^*(\xi) \end{cases}. \tag{11}$$

This profit function in (11) is a crucial object in our analysis, because it determines the *marginal* return to expansion. In particular, as discussed above, as long as firms do not delegate, the marginal profit from an additional market is declining, i.e., $\tilde{\pi}(n)$ is *concave* in n. Once firms reach the critical size n^* and start hiring outside managers, however, the profit function becomes *linear* in the number of markets n. Hence, entrepreneurs can overcome the decreasing returns to scale by delegating managerial tasks to outside managers. Moreover, conditional on delegating, an increase in delegation efficiency ξ increases the slope of the profit function for any given ω_M. This is illustrated in Figure 1, where we depict (11) for given ω_M.

Consider first Panel A in Figure 1. Small firms are run only by their owner and hence subject to diminishing returns as in Lucas (1978). By delegating authority, the firm can increase the supply of managerial services, and hence prevent marginal profits from declining. In particular, firms' optimal hiring policy in (10) implies that the resulting managerial services per product are given by $e(n) = \max\left\{\frac{T}{n}, \frac{T}{n^*}\right\}$. Hence, delegation allows firms to expand at a given managerial

Figure 1: Delegation and Decreasing Returns To Scale



Notes: In Panel A we depicts the profit function $\tilde{\pi}(n)$ characterized in (11). In Panel B we consider an increase in ξ and depict the change in the profit function $\tilde{\pi}(n)$ for given wages ω_M.

intensity. This implies that, once the firm size hits the delegation cutoff $n^*(\xi^L)$, the profit function becomes linear as in the baseline version of Klette and Kortum (2004). In Panel B we illustrate an increase in the delegation efficiency from ξ^L to ξ^H. If delegation becomes more efficient, both the delegation cutoff declines and the slope of the profit function increases. In particular, a higher delegation efficiency raises the returns to being large and therefore affects firms' expansion decisions. Quantifying this relationship between delegation efficiency and firm growth will be one focus of our quantitative analysis in Section 4.

Supply of Outside Managers To parametrize the supply of outside managers, we assume that there is a unit measure of individuals who can work either as production workers or managers. Each individual is endowed with a single unit of production labor and h_M units of managerial human capital. For simplicity, we assume that h_M is drawn from a Pareto distribution, i.e., $P(h_M > h) = \left(\frac{\vartheta-1}{\vartheta}\mu_M\right)^{\vartheta} \times h^{-\vartheta}$. Here μ_M parametrizes the average level of managerial skills relative to workers (note that $E[h_M] = \mu_M$) and ϑ governs the heterogeneity in managerial talent.

Given the production wage w_P and the managerial wage w_M, the individual decides to be a manager if and only if $h_M w_M \geq w_P$. The total labor supply of production workers H^P and managers H^M in efficiency units is therefore given by

$$H^P = 1 - \left(\frac{\vartheta-1}{\vartheta}\mu_M\right)^{\vartheta}\left(\frac{w_M}{w_P}\right)^{\vartheta} \quad \text{and} \quad H^M = \left(\frac{\vartheta-1}{\vartheta}\mu_M\right)^{\vartheta}\left(\frac{w_M}{w_P}\right)^{\vartheta-1}\frac{\vartheta}{\vartheta-1}. \tag{12}$$

Hence, the supply of managerial human capital is increasing in the relative wage, with an elasticity of $\vartheta - 1$.[8] Moreover, holding relative wages fixed, managerial skill supplies are increasing

[8]Note that ϑ must be greater than 1 for average human capital to be finite.

in μ_M. Finally, the share of individuals working as managers is given by

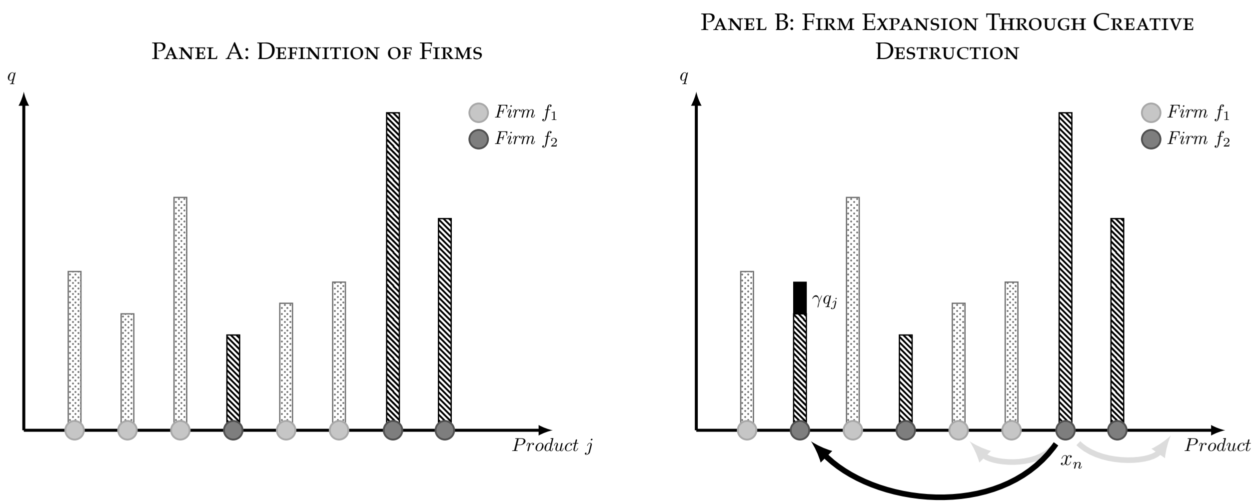
$$M = P\left(h_M \geq \frac{w_P}{w_M}\right) = 1 - H^P = \left(\frac{\vartheta - 1}{\vartheta}\mu_M\right)^{\vartheta}\left(\frac{w_M}{w_P}\right)^{\vartheta}. \quad (13)$$

The managerial employment share M will be an important calibration target for our quantitative exercise below, because it will be informative about cross-country differences in managerial skills μ_M and delegation efficiency ζ, which will be reflected in the relative managerial wage $\frac{w_M}{w_P}$.

2.3 Firm Dynamics: Expansion, Entry, and Exit

Consider now the dynamic aspects of firm behavior. Our model is a model of creative destruction where firms grow by stealing products from their competitors and decline in size if other firms replace them as the most productive producer in a particular market. As an example of this, process consider Figure 2. In Panel A we illustrate an example, where firm f_1 is the current producer in five markets and firm f_2 in three markets. Either firm can expand in market j' by introducing better versions of the technology of what the current incumbent in j' uses.

Figure 2: Firms, Expansion and Creative Destruction



Notes: In Panel A we depict two examples of firms in this economy. While firm 1 is the producer in five markets, firm 2 is the most efficient firm in three products. In Panel B we depict the process of creative destruction: firm 2 successfully replaces firms 1 in market j by increasing the productivity frontier.

Formally, if a firm with n products in its portfolio invests R units of the final good, it generates a flow rate of innovation equal to

$$X\left(R; \theta, n\right) = \theta[R/Q]^{\zeta} n^{1-\zeta}, \quad (14)$$

where Q is defined as the aggregate productivity index

$$Q \equiv \exp\left[\int_0^1 \ln q_{jt} dj\right]. \tag{15}$$

In (14), θ determines the efficiency of innovation, $\zeta < 1$ parametrizes the concavity of the innovation production function and the other terms are the usual scaling variables required in all models of endogenous growth.[9] Conditional on innovating, the firm improves the productivity of a randomly selected product j by a multiple $\gamma > 1$ and replaces the existing firm as the producer of product j. An example of this process is illustrated in Panel B of Figure 2: firm f_2 successfully expands into the second market of firm f_1 by increasing the productivity frontier in that market from q_j to γq_j.

A central parameter for our analysis is θ, which determines the firm's growth potential. Importantly, we assume that firms *differ* in their growth potential and can be either *transformative* (high, θ_H) or *subsistence* (low, θ_L) types. A firm's type is persistent and determined upon entry. Formally, each new entrant draws a firm type $\theta \in \{\theta_H, \theta_L\}$ from a Bernoulli distribution, where

$$\theta = \begin{cases} \theta_H & \text{with probability } \alpha \\ \theta_L & \text{with probability } 1-\alpha \end{cases}. \tag{16}$$

It is this heterogeneity across producers, which gives rise to the possibility of *selection*, whereby low-type producers are replaced by their more dynamic high-type counterparts.

To capture the existence of subsistence entrepreneurs, we set that $\theta_L = 0$ in (14), so that low-type firms are entirely stagnant and will never be able to grow. This polar case is conceptually useful because it stresses that low types are never supposed to grow. Hence, the sole difference in firm dynamics across countries will stem from the innovation incentives for high types and it will be high types' appetite for expansion that will determine the degree of selection, i.e., the time it takes for entering low-type firms to be replaced.

To characterize the optimal expansion policies of high-type firms, which are forward looking, we need to solve for their value functions. The value of a high-type firm with n products, $V_H(n)$, solves the continuous time Hamilton-Jacobi-Bellman equation:[10]

$$\rho V_H(n) = \Pi(n) + n\tau_H \left[V_H(n-1) - V_H(n)\right] + \max_X \left\{ X\left[V_H(n+1) - V_H(n)\right] - Qn^{\frac{\zeta-1}{\zeta}} \left[\frac{X}{\theta_H}\right]^{\frac{1}{\zeta}} \right\}. \tag{17}$$

The flow value of the firm consists of three parts. First of all, the firm earns the flow profits

[9] Because we denote innovation costs in terms of the final good, the growing scaling variable Q is required to keep the model stationary. We also assume that firms' innovation costs depend on the number of products n to generate deviations from Gibrat's law solely through incomplete delegation. In particular, if the value function was linear, e.g. as in Klette and Kortum (2004), the specification in (14) would imply that firm growth was independent of size.

[10] Because we focus on a stationary equilibrium, (17) is already derived under the restriction that $V_s(n)$ grows at the endogenous but constant economy-wide growth rate g such that $rV_s(n) - \dot{V}_s(n) = (r-g)V_s(n) = \rho V_s(n)$. Note that this last equality follows from the household's Euler equation (1).

$\Pi(n)$ given in (11). Secondly, the firm might lose one of its products to other firms. This occurs with the endogenous rate of creative destruction $n \times \tau_H$, which we allow to be type-specific (see below). Finally, the value function incorporates the option value of expansion, which is the last term in (17): the firm experiences a capital gain $V_H(n+1) - V_H(n)$ with flow rate X but has to pay the associated innovation costs stemming from (14).

Let us denote the innovation intensity (innovation per product line) by $x_n \equiv X(n)/n$. Equation (17) then implies that the optimal innovation intensity x_n is given by

$$x_n = \theta_H^{\frac{1}{1-\zeta}} \zeta^{\frac{\zeta}{1-\zeta}} \times \left(\frac{V_H(n+1) - V_H(n)}{Q} \right)^{\frac{\zeta}{1-\zeta}}. \tag{18}$$

Naturally, the incentives to grow depend on the *marginal* returns of doing so, $V(n+1) - V(n)$. It is this marginal return that links firms' innovation incentives to the delegation environment. In equation (11) and Figure 1 we showed that the delegation efficiency ξ will determine the *concavity* of the profit function and hence the marginal flow profit of expansion. Because the value function inherits the properties of the profit function, the delegation efficiency will also determine the *slope* of the value function and hence the optimal innovation rate for firms of different size. The lower the delegation efficiency ξ, the more concave is the resulting value function and more will innovation incentives decline in firm size. Intuitively, if firms anticipate that they will not be able to efficiently delegate decision power once they reach a size where delegation becomes essential, their incentives to expand diminish. A higher delegation efficiency ξ will therefore *increase* firms' expansion incentives by increasing the slope of the value function.

Similarly, we can also express the value function of a low-type firm as

$$\rho V_L = \Pi(1) + \tau_L [0 - V_L], \tag{19}$$

as subsistence entrepreneurs have a single product, which they lose at rate τ_L, and never expand.

Endogenous Entry A unit mass of potential entrants attempt to enter the economy every period using the same innovation technology as incumbent firms,

$$z = \theta_E [R_E/Q]^{\zeta}, \tag{20}$$

where z is the entry flow rate and R_E is amount of final goods spent on entry efforts. Entrants enter the economy with a single product and the realization of θ is revealed only after the entry costs have been paid. Recall from (16) that an entrant becomes a high type producer with probability α. Then the maximization problem of a potential entrant is simply

$$\max_z \left\{ z [\alpha V_H(1) + (1-\alpha) V_L] - Q \theta_E^{-\frac{1}{\zeta}} z^{\frac{1}{\zeta}} \right\},$$

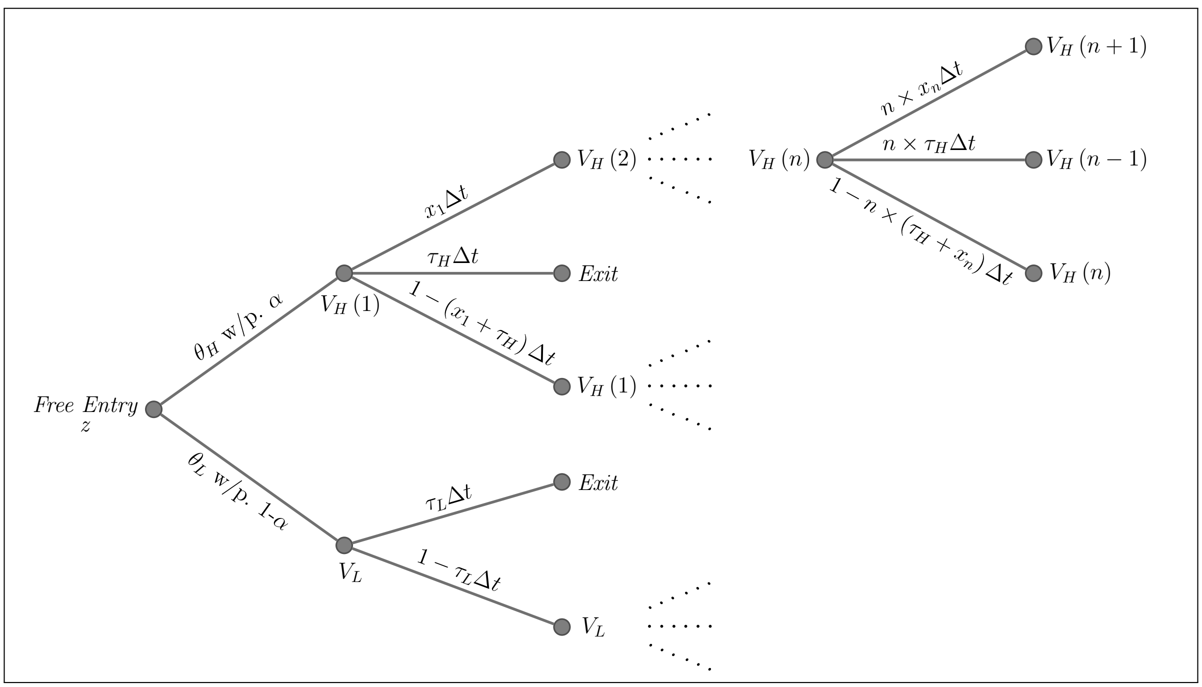
where $V_H(1)$ is implicitly defined in (17) and $V_L = \frac{\Pi(1)}{\rho + \tau_L}$ from expression (19). The equilibrium entry rate is then given by

$$z=\theta_E^{\frac{1}{1-\zeta}}\zeta^{\frac{\zeta}{1-\zeta}}\left[\frac{\alpha V_H\left(1\right)+\left(1-\alpha\right)V_L}{Q}\right]^{\frac{\zeta}{1-\zeta}}. \tag{21}$$

2.4 Stationary Equilibrium

Figure 3 provides an overview of the firms' life cycle dynamics in our model. Firms enter the economy with a single product and are either transformative, high-type entrepreneurs (with probability α) or subsistence, low-type entrepreneurs (with probability $1-\alpha$). The corresponding value functions are $V_H(1)$ and V_L. Within the next time interval Δt high-type firms either expand (at rate x_1), lose their only product and exit (at rate τ_H) or remain a one-product firm. Low type firms in contrast never expand but either exit the economy (at rate τ_L) or remain in the economy by serving their initial market.

Figure 3: Overview of the Life-Cycle Dynamics in the Model



Notes: This figure summarizes the life-cycle dynamics of our model. Upon entry firms are high types with probability α and low types with probability $1-\alpha$ [see equation (16)]. $V_H(n)$ and V_L denote the value functions in (17) and (19), x_n is the optimal innovation rate given in (18), and τ_H and τ_L are the endogenous rates at which high and low-type firms lose their markets to other firms.

We focus on the stationary (or balanced growth path) equilibrium of this economy, where all aggregate variables grow at a constant rate and the firm size distribution is stationary. In our model the firm size distribution is characterized by the mass of firms of type s, F^s, and the share of type-s firms with n products, $[\nu_n^s]_{n=1}^{\infty}$. In particular, the mass of firms producing n products is given by $\varphi_n = F^H \nu_n^H + F^L \nu_n^L$.[11] A stationary equilibrium is therefore defined as follows.

Definition 1 *Consider the environment described above. A stationary equilibrium is a tuple*

$$\{p_j, y_j, V_H(n), V_L, x_n, z, w_M, w_P, \nu_n^H, F^H, F^L, r, g\}$$

such that (i) $[p_j, y_j]$ maximize monopoly profits in (5), (ii) the value functions $[V_H(n), V_L]$ are given by (17) and (19), (iii) the innovation rates x_n maximize those value functions in (18), (iv) the entry rate z solves the entrant's maximization problem (21), (v) w_P clears the production labor market and w_M clears the managerial labor market, (vi) firm-type shares $[F^H, F^L]$ and firm size distributions ν_n^H are stationary and consistent with the innovation and entry rates, (vii) the constant interest rate is given by (1), and (viii) the aggregate growth rate is consistent with the innovation rates.

2.4.1 Labor Market

The Cobb-Douglas final good production function together with the market structure described in Section 2.1 implies that the total number of production workers hired for variety j by a producer, who is active in n markets, is given by[12]

$$l_j = [\omega_P \mu(e)]^{-1} = \omega_P^{-1} \times (1 - e(n)^{\sigma}).$$

Using firms' optimal delegation policy and aggregating over the firm size distribution yields the aggregate demand for production workers

$$H^P = \left[1 - \sum_{n=1}^{\infty} \left(\max\left\{\frac{T}{n}, \frac{T}{n^*}\right\}\right)^{\sigma} \times n \times \varphi_n\right] \times \omega_P^{-1} \tag{22}$$

Similarly, firms' managerial demand function in (10) implies that the aggregate demand for managers is given by

$$H^M = \sum_{n \geq n^*}^{\infty} n \times m(n) \times \varphi_n = \left(\frac{\sigma}{\omega_M}\right)^{\frac{1}{1-\sigma}} \xi^{\frac{\sigma}{1-\sigma}} \sum_{n \geq n^*}^{\infty} n\varphi_n - \frac{T}{\xi} \sum_{n \geq n^*}^{\infty} \varphi_n. \tag{23}$$

Note that (23) reveals the complementarity between firm size and managerial demand: For given prices, managerial demand will be higher the bigger the importance of large firms. Labor market clearing requires that labor supply in (12) is equal to labor demand in (22) and (23). These conditions determine equilibrium wages (ω_P, ω_M) (for a given distribution of firm size).

[11] Note that $\nu_n^L = 0$ for all $n > 1$.

[12] To see this, note that $Y = p_j y_j = \frac{w_P}{q_j} q_j \mu(e_j) l_j$ and $\omega_P = w_P / Y$.

2.4.2 Aggregate Innovation and Growth

As in any model of creative destruction, firms enter the economy and expand into new markets at the direct expense of other producers. Hence, the intensity with which a type-s firm ($s \in L, H$) loses its products, τ_s, is endogenously determined. In a stationary equilibrium, firms' innovation incentives x_n and the entry rate z are constant, i.e., they might be a function of firm size but they are not time dependent. Denote the aggregate rate of innovation by τ. Innovations can happen through entering firms or through the expansion of incumbent firms, whereby high-type incumbents with n products expand at rate nx_n. Therefore,

$$\tau \equiv \sum_{n=1}^{\infty} x_n n \times F^H \nu_n^H + z, \tag{24}$$

as low-type firms never expand. The following lemma shows that the equilibrium growth rate of the economy is proportional to the aggregate rate of innovation and depends on the step size γ.

Lemma 1 *Let τ denote the aggregate rate of innovation and g denote the growth rate of aggregate output Y. Then*

$$g = \tau \ln(\gamma).$$

Proof. See Appendix A.1. ■

2.4.3 Selection and the Firm Size Distribution

Our model allows firms to differ in their innovativeness, i.e., the rate at which they expand into new product lines. Similarly, firms could also differ in the rate at which they lose markets due to differences in their reputation, customer loyalty, or organizational capital. Therefore we also allow for the possibility that the rate of creative destruction might be type specific and calibrate the extent to which this is the case. Formally, we let

$$\tau_L = \beta \tau_H,$$

where β captures potential differences in creative destruction across firm types. If $\beta > 1$, low-type firms are easier to replace (or are targeted by expanding firms more intensely), if $\beta < 1$, the opposite is the case. Consistency requires that the total amount of innovation has to be equal to the total rate of creative destruction:

$$\tau = \tau_H(1 - F^L) + \tau_L F^L, \tag{25}$$

as F^L is the share of products which is produced by low-type firms (all of which have only a single product, i.e., $\nu_1^L = 1$). The following proposition shows that the firm size distribution has a closed form expression and can be calculated from firms' innovation and entry policies $[x_n]_n$ and z.

Proposition 1 *Consider a stationary equilibrium and let the flow of entry z and high-type firms' expansion rates $[x_n]_n$ be given. The distribution of high-type firms is*

$$\nu_n^H = \frac{n^{-1}\frac{\tau_H}{x_n}\prod_{j=1}^n\left(\frac{x_j}{\tau_H}\right)}{\sum_{s=1}^{\infty} s^{-1}\frac{\tau_H}{x_s}\prod_{j=1}^s\left(\frac{x_j}{\tau_H}\right)}, \tag{26}$$

the measure of high- and low-type firms is

$$F^H = \frac{\alpha z}{\tau_H} \times \left[\sum_{n=1}^{\infty} \frac{\tau_H}{n x_n} \prod_{j=1}^{n} \left(\frac{x_j}{\tau_H}\right)\right] \quad \text{and} \quad F^L = \frac{(1-\alpha)z}{\tau_L}, \tag{27}$$

the aggregate rate of innovation is

$$\tau = z \times \left[\alpha \sum_{s=1}^{\infty} \prod_{j=1}^{s} \left(\frac{x_j}{\tau_H}\right) + 1\right], \tag{28}$$

and the type-specific creative destruction rates are

$$\tau_H = \tau - z\left(1-\alpha\right)\left(\frac{\beta-1}{\beta}\right) \quad \text{and} \quad \tau_L = \beta\tau - z\left(1-\alpha\right)\left(\beta-1\right). \tag{29}$$

Proof. See Appendix A.2. ∎

Proposition 1 constructs the unique distribution of firm size and the number high- and low-type producers explicitly. In particular, given $[x_n]_n$ and z, the aggregate rate of innovation τ and the type-specific creative destruction rates τ_H and τ_L can be explicitly calculated from (28) and (29). The number of firms (F^L, F^H) and the distribution of firm size ν_n^H then follow directly from (26) and (27).

The results in Proposition 1 precisely illustrate the link between the delegation environment and the resulting firm size distribution. Specifically, consider a decline in delegation efficiency ξ holding all wages and the flow rate of entry z constant. This will reduce managerial hiring (both on the intensive and extensive margins from expressions (9) and (10)) and lower firms' *marginal* profits conditional on delegating, and hence the slope of value function and their expansion rates $[x_n]$. Intuitively: If firms anticipate to not be able to hire outside managers once they reach the delegation cutoff n^* in the future, their incentives to expand today are low.

This decline in innovation incentives will affect the firm size distribution and degree of selection. First of all, note that (28) and (29) imply that the rates of creative destruction (τ, τ_H, τ_L) will decline. This has the direct implication that low-type firms will survive *longer*. As such producers lose their only market at rate τ_L, the probability of a given low-type firm still being around at age a is simply $e^{-\tau_L \cdot a}$. Hence, while all low-type firms exit the economy eventually, this weeding-out process runs its course faster, the higher the rate of creative destruction τ_L. The fact that stagnant firms in poor countries survive for a long time is therefore consistent with the view that efficient firms generate too little creative destruction to drive them out of the market quickly. For the aggregate economy, this implies that the number of low-type producer F^L is also going to be larger, as illustrated in (27).

Secondly, because large firms are particularly reliant on outside managers, a decline in delegation efficiency will have a disproportionate effect on expansion incentives of large firms. Hence, large firms will cut down on their expansion efforts *relatively* more. This implies, through equation (26), that the firm size distribution shifts to the left so that a larger share of economic activity will be generated in small firms. From the point of view of a plant's life cycle, this particular deviation from Gibrat's law implies that large firms will grow at a lower rate than small firms, so that age is less a predictor of size. This is qualitatively consistent with the cross-country evidence.

The above intuition neglects two countervailing general equilibrium forces. First of all, the change in the firm size distribution due to a change in ξ will induce a decline in managerial wages to ensure labor market clearing. Secondly, there will be a change in entry. Theoretically, the response of entry to a decline in ξ is ambiguous: while the value of being a high-type firm $V_H(1)$ tends to decline (after all, it is the high-type producers that are eventually harmed by an inability to delegate), low-type firms in fact *benefit* from an inefficient delegation environment! While they do not expect to hire outside managers themselves, the decline in creative destruction τ_L will *increase* their expected life-span and hence V_L. To fully characterize the effects of changes in the delegation environment on the process of firm dynamics we therefore turn now to the quantitative analysis.

3 Data and Empirical Analysis

In Section 4, we will take the model to the data to quantify the importance of cross-country differences in the delegation efficiency ξ. Before we do that, in Section 3.1 we describe the data that we are going to use. In Section 3.2 we look at some basic correlations in our data, as a first pass, to study the empirical validity of our theoretical framework.

3.1 Data

Our quantitative analysis uses both plant-level and individual-level micro data. To measure properties of the process of firm dynamics, we rely on micro data for the population of manufacturing plants in the U.S. and India.[13] We then combine this information with individual-level census records from both countries to measure the importance of managerial employment. Here we briefly describe the main data sources. A detailed description of all our data sources is contained in Section B.1 in the Appendix.

[13] A comparison of firm-level vs plant-level data for the U.S. is included in Section OA-2.1 of Online Appendix. Moreover, Section 5.6 provides the main quantitative results based on firm-level data.

Plant level data for the U.S. and India We calibrate our model to data for the manufacturing sector of the U.S. and India. For the case of the U.S. we rely on publicly available data from the Business Dynamics Statistics (BDS). The BDS is provided by the U.S. Census Bureau and compiled from the Longitudinal Business Database (LBD), which draws on the Census Bureau's Business Registry to provide longitudinal data for each plant with paid employees. This data has also been used in Haltiwanger et al. (2013) and Moscarini and Postel-Vinay (2012). We focus on the data from 2012. As for India, we follow Hsieh and Klenow (2014) and Hsieh and Olken (2014) and use the Annual Survey of Industries (ASI) and the National Sample Survey (NSS). The ASI focuses on the formal sector and covers all plants employing ten or more workers using electric power and employing twenty or more workers without electric power. To overcome this oversampling of large producers in the ASI, we complement the ASI with data from the NSS, which (every five years) surveys a random sample of the population of manufacturing plants without the minimum size requirement of the ASI. We merge these two datasets using the sampling weights provided in the data and focus on the year 2010, which is the latest year for which both data sets are available. Both to be consistent with the existing literature [e.g., Hsieh and Klenow (2014)] and because the Indian data is collected at the level of the establishment, we focus on individual plants and not firms. We will conduct robustness checks using firm-level data in Section 5.[14]

Table 1 contains some basic descriptive statistics about the distribution of plant size in the U.S. and India. The importance of large firms varies enormously between countries. In the U.S., two-thirds of manufacturing employment is concentrated in plants with at least 100 employees and only one-third of the plants have fewer than 4 employees. In India, more than nine out of ten plants have fewer than four employees and they account for more than half of aggregate employment. Given our theory, these numbers are suggestive of a lack of selection, whereby subsistence firms survive because few firms in India manage to reach a size exceeding one hundred employees.

Table 1: Plant size in the U.S. and India

		1 - 4 employees		$\geq$ 100 employees	
	Mean empl.	Share	Empl. share	Share	Empl. share
U.S.	42.7	32.8%	1.8%	8.8%	65.6%
India	2.7	93.0%	54.8%	0.1%	18.6%

Notes: The table contains summary statistic from the firm size distribution in the U.S. and India. The U.S. data come from the BDS in 2012, the data for India from the NSS and ASI in 2010.

[14] The BDS uses a unified treatment of plants and firms. While a plant is a fixed physical location where economic activity occurs, firms are defined at the enterprise level such that all plants under the operational control of the enterprise are considered part of the firm.

Data on Managerial Employment To infer countries' delegation efficiency, we require data on the equilibrium level of managerial employment. Such data is available from the national census data provided by the IPUMS project. For each country we get a sample from the census, which has detailed information about individual characteristics. We observe each respondent's education, occupation, employment status, sex and industry of employment. We focus on male workers in the manufacturing industry working in private-sector jobs. We always use the most recent data available, which is 2004 in the case of India and 2010 in the case of the U.S.

To classify workers as managers in the sense of our model, we use information about workers' occupational status and employment status. As our theory stresses the importance of delegating authority to *outside* managers, we classify employees as managers if they got assigned the occupational code "Legislator, Senior official and manager" *and* they are hired as wage workers instead of being, for example, family members of the firms' owner or the employer themselves. As seen in Table 2, outside managers are relatively rare in India: only 1.7% of the male manufacturing workforce work as managers for a wage. The corresponding number in the U.S. is 12.4%.

Table 2: Outside Managers in India and the U.S.

	U.S.	India
Share of outside managers	12.4	1.7

Notes: The table contains the share of outside managers in the manufacturing sector in the U.S. and India. Outside managers are all managers, according to the occupation classification ISCO, that are hired as wage workers. We focus on male workers in private-sector jobs.

The distinction between being hired for a wage and being self-employed or a family member is important. In the U.S. almost 90% of managers are wage workers and hence outside managers in the sense of our theory. This is very different in the case of India. Conditional on being in a managerial occupation, only 12% of individuals are wage workers and the vast majority of individuals working in managerial occupations are either entrepreneurs themselves or unpaid family members. The latter is consistent with the findings in Bloom et al. (2013), who also argue that Indian firms acquire managerial services mostly from their owners or close family members. This pattern is very much the exception in the U.S.

3.2 Empirical Correlations in the Micro Data

Before we move on to the quantitative analysis, we find it useful to present some relevant correlations in the Indian micro data, which can shed light on the basic mechanism in the theory. In particular, the Indian micro data provides us with information on managerial hiring patterns, firm size and various entrepreneurial characteristics. Using this data, we can study the determinants of firm size and the demand for outside managers.[15]

Our theory, especially equation (9), implies that firms' managerial hiring decision is given by

$$m_j = 0 \quad \text{if} \quad n < n^* \equiv T\left(\frac{\omega}{\sigma\xi}\right)^{\frac{1}{1-\sigma}}.$$

Hence, firms are more likely to delegate if (i) firm size n increases, (ii) the delegation environment ξ improves, and (iii) owner's inelastically provided managerial human capital T is smaller.

To take this prediction to the data, we follow Bloom et al. (2013, p. 4), who argue that for Indian textile firms "managerial time was constrained by the number of male family members. Non-family members were not trusted by firm owners with any decision-making power, and as a result firms did not expand beyond the size that could be managed by close (almost always male) family members." Hence, we take the size of the entrepreneurs' family as a proxy for T[16] and use regional variation in trust within India as inducing variation in ξ. The latter is calculated from the World Value Survey as the share of people providing the answer "Most people can be trusted" within the Indian state where the firm is located. This is the most common measure of trust used in the literature [see for instance, Bloom et al. (2012) and La Porta et al. (1997)].

More specifically, we regress firms' managerial hiring decision on firm size, household size and regional trust (in 22 Indian states).[17] We always control for the market of a firm, i.e., whether or not the firm is urban or rural, firm age, state-level GDP per capita, and 2-digit sector fixed effects. Due to space constraints, below we provide only the estimated equation; the full analysis can be found in Appendix B.4. We find that

$$\mathbb{1}\left[\textbf{Manager>0}\right] = \underset{(0.003)^{***}}{0.039} \times \textbf{Firm\_Size} \; \underset{(0.001)^{**}}{-0.003} \times \textbf{Family\_Size} \; \underset{(0.006)^{***}}{+0.013} \times \textbf{Trust},$$

where $\mathbb{1}\left[\textbf{Manager>0}\right]$ is an indicator variable whether the firm hires a manager and "Firm_Size" and "Family_Size" are the logarithms of the number of employees and household members, respectively. This regression shows that firm size and regional trust correlates positively, whereas family size correlates negatively, with the probability of hiring an outside manager. These effects are also economically large. A one standard deviation increase in firm size is associated with an increase in the probability of managerial hiring by 110% $\left[= \frac{0.039\times0.463}{0.0167}\right]$ relative its sample mean. Likewise, adding one more person to a single-person household is associated with a decrease in the managerial hiring by 13% $\left[= \frac{0.003\times0.69}{0.0167}\right]$ and moving from the lowest trust region to highest trust region in India is associated with an increase in managerial hiring by 37% $\left[= \frac{0.013\times(0.628-0.156)}{0.0167}\right]$ relative to the sample mean. These findings are, at least qualitatively, in line with the theoretical predictions of the model.

Our model also has implications on the relationship between family size and firm size, which

[15] See Section B.4 for the details of the empirical analysis and robustness.

[16] Our data does not have information on either age or sex of the entrepreneur's children.

[17] In Appendix B.4, we provide an explicit derivation of the regression equation based on the theory.

was emphasized in the quotation by Bloom et al. (2013) above. In our model, without delegation, firm owners run into span-of-control problem as managerial resources within the family, T, are the constraining factor. This constraint, however, is *less* important, the higher the delegation efficiency ξ is. Hence, while family size should be a predictor of firm-size, the effect should be particularly strong in regions where trust, and hence the possibility of delegation, is *less* developed. Allowing for this interaction between trust and family size, we find that:[18]

$$\textbf{Firm\_Size} = \underset{(0.306)^{***}}{0.927} \times \textbf{Family\_Size} - \underset{(0.818)^{**}}{1.694} \times [\textbf{Family\_Size} \times \textbf{Trust}] + \underset{(1.628)^{**}}{3.264} \times \textbf{Trust}$$

This regression highlights two key empirical findings. First, in line with Bloom et al. (2013), we find a strong positive correlation between family size and firm size. Indeed, a 1% increase in family size is associated with 0.34% $[= 0.927 - 1.694 \times 0.347]$ increase in firm size in a region with an average level of trust. The second interesting finding is that the same elasticity increases to 0.66% $[= 0.927 - 1.694 \times 0.156]$ when we move to the lowest-trust region. Hence, the link between family size and firm size is much stronger in low-trust regions. Through the lens of our model, this would happen due to the imperfections in delegation in those regions.[19]

4 Delegation and Firm Dynamics in the U.S. and India

In this section we turn to our quantitative analysis of the differences in firm dynamics between India and the U.S. To this end, we take the following approach. In order to understand why Indian firms look different than their U.S. counterparts and whether such differences are indicative of a low level of creative destruction and selection, we independently calibrate our model to the Indian data and the U.S. data, i.e., we allow the key parameters of our theory to differ between these economies. By doing so we capture various mechanisms determining the process of firm-dynamics, albeit in a parsimonious way.

First of all, consider capital market imperfections: if firms need to borrow to be able to increase their productivity and expand, frictions in the Indian financial system might prevent firms from investing in lucrative technologies and hence cause many firms to remain small [see, for instance, Cole et al. (2016)]. Second, firms in India could be subject to size-dependent policies, whereby (implicit) tax rates increase in firm size due to stricter regulatory control or larger overhead costs like non-wage benefits. Such frictions will also reduce firms' incentives to grow large and mechanisms along these lines have been explored in Hsieh and Klenow (2014), Guner et al. (2008), Ulyssea (2016), and Bento and Restuccia (2017). Third, frictions on Indian product market

[18] As before, we also control for location of the firm (rural vs. urban), firm age, state-level GDP per capita, and 2-digit sector fixed effects.

[19] The effect of trust is weaker if we control for 3-digit sector fixed effects instead of 2-digit: the point estimates are very similar but the effect of trust becomes insignificant. This is mainly due to fact that, given relatively small sample size, finer controls for sector fixed effect leave less variation in the data for the relations we are interested in. See Section B.4 in the Appendix for more details.

[e.g., Foster et al. (2016), Gourio and Rudanko (2014), and Perla (2016)] or higher transportation costs would also discourage firm expansion and keep Indian firms small. In our model, we capture such explanations by allowing Indian firms to potentially face high costs of expansion ($\theta_{IND} < \theta_{US}$).

Similarly, inefficiencies in the allocation of start-up capital or frictions in labor markets might induce unproductive firms to enter, causing a larger share of subsistence entrepreneurs in India. If this is an important aspect of the firm-level data, our model should estimate low-type firms in India to be plentiful upon entry ($\alpha_{IND} < \alpha_{US}$). Finally, the Indian economy might be characterized by higher entry costs due to bureaucratic red tape. Our model allows for this margin through variation in the efficiency of entry ($\theta^E_{IND} < \theta^E_{US}$).

While allowing for such differences is obviously important if one wants to account for structural differences between the U.S. and India, doing so is also crucial to credibly measure the relationship between delegation efficiency ξ and the resulting firm dynamics. First, controlling for these other factors is important for our identification strategy. Many of the above mechanisms can potentially explain why firms in India might be small. To the extent that such differences are correlated with inefficiencies in the process of delegation, we want to control for these determinants of firm dynamics to isolate the direct effect of the delegation efficiency. Similarly, an important empirical moment to identify differences in the delegation efficiency is the observed difference in the importance of outside managers. Given the complementarity between managerial hiring and firm size, any of these mechanisms above could in principle explain differences in the extent of managerial hiring by keeping firms small. By allowing the distribution of firm size in India to be different than in the U.S., we effectively control for such other differences in managerial demand and identify ξ only from the variation in aggregate managerial employment shares, *which is not explained by such alternative mechanisms*. Second, delegation efficiency ξ and the efficiency of expansion θ are complements, since delegation becomes more essential as firms grow large. The effect of a change in ξ on the process of firms dynamics therefore depends directly on the other structural parameters. As we show below, such complementarities turn out to be quantitatively important in our context.

4.1 Identification

Our model has 12 parameters: $\{\xi, \sigma, T, \mu_M, \vartheta, \theta, \theta_E, \zeta, \alpha, \beta, \gamma, \rho\}$. Five parameters directly relate to the demand and supply of managerial services: the delegation efficiency ξ, the managerial output elasticity σ, and the owners' own human capital T determine managerial demand for a given size of the firm. The supply of managerial skills is governed by the two parameters of the skill distribution μ_M and ϑ. The technology of firm dynamics is captured by three parameters: innovation and entry efficiencies θ and θ_E and the convexity of the cost function ζ. The underlying heterogeneity of firm types is affected by the share of high-type entrants α and difference in type-specific creative destruction rates β. Finally, we need to parametrize the innovation step size γ and discount rate ρ.

We fix two of the parameters exogenously as we describe below (ρ and ζ) and the remaining 10 parameters are estimated by minimizing the distance between several empirical moments and their model counterparts. Let us define the parameter set as

$$\Omega \equiv \{\xi, \sigma, T, \mu_M, \vartheta, \theta, \theta_E, \alpha, \beta, \gamma\}.$$

Let M^E denote the vector of empirical moments and $M(\Omega)$ denote the vector of model-simulated moments for a given Ω. We minimize the following loss function by searching over the possible values of Ω:

$$\min_{\Omega} \sum_{m=1}^{11} \frac{|M_m^E - M_m(\Omega)|}{|M_m^E|}.$$

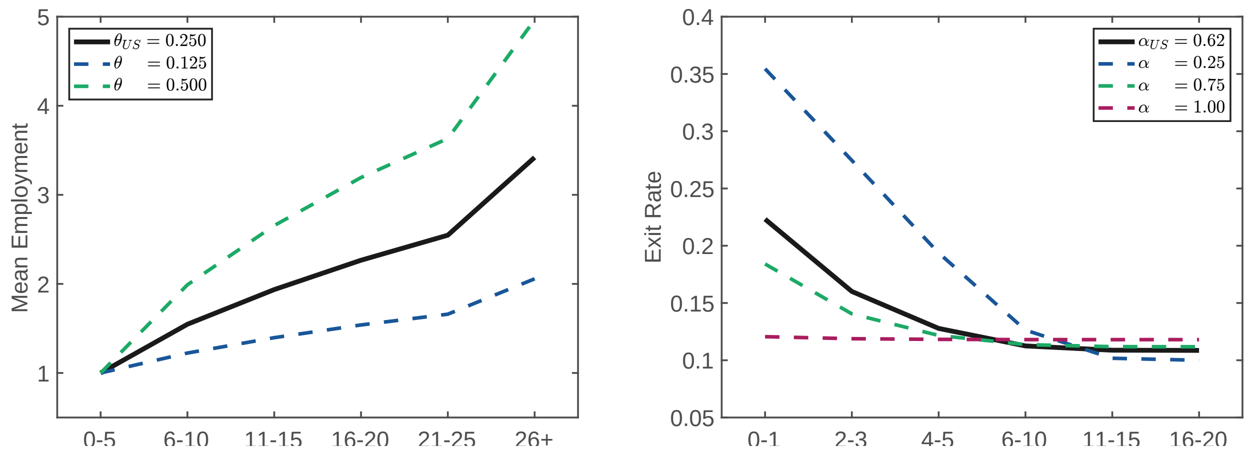
Even though our parameters are estimated jointly and most of the target moments cannot be expressed analytically, our aim is to be transparent about the parameter identification. Therefore, we proceed in two steps. First, below we provide a heuristic description about the relationship between the parameters and specific moments. Second, in Appendix B.2, we not only provide a more formal identification discussion but we also verify these relationships numerically using a sensitivity matrix, where we report the elasticity of each moment used in the internal calibration with respect to the parameters of the model (see Table 16). [20]

Identifying θ, α, and β. Consider first the identification of θ, α, and β, i.e., the main parameters governing the non-managerial aspects of firm-growth. The expansion efficiency θ is mostly identified from differences in the profile of firms' life-cycle growth, i.e., the extent to which firms grow as they age, between the U.S. and India. To see that, consider the left panel of Figure 4, where we depict mean employment by firm age for three different levels of θ: the higher θ, the steeper the life-cycle profile. For the share of high-type producers α, we focus on the age-profile of exit rates conditional on firm size. Note that without type heterogeneity, the likelihood of exit would be independent of age conditional on size. In the data, however, exit rates are strongly decreasing in firm age conditional on size [see e.g., Haltiwanger et al. (2013)]. Through the lens of our model, this pattern is rationalized through endogenous selection, whereby the share of high-type firms within a given cohort increases as the cohort ages. This pattern is depicted in the right panel of Figure 4. When there is no heterogeneity in growth potential, i.e., $\alpha = 1$, the conditional exit-age relationship is flat (as shown in the red, dashed line). With heterogeneity, the slope becomes downward sloping as older cohorts are positively selected. Finally, the parameter β, which determines how quickly low-type firms lose market share relative to high-type competitors, is identified from the aggregate employment share of old firms. Intuitively, as high-type firms are older on average, the aggregate size of old cohorts is informative about this parameter.

[20] In particular, we report percentage change in the moment for a 1% change in the parameter from its benchmark calibrated value, while keeping the rest of the parameters at their benchmark values. We report the average elasticities based on +1% and -1% changes.

Figure 4: Identification of α and θ

Panel A: The Life-Cycle — Panel B: Exit Rate of Small Firms by Age



Notes: The left panel shows the employment life-cycle, i.e., average employment by age, for different values of θ. The right panel shows the exit rate of one-product firms by age for different values of α. The black line depicts the U.S. calibration (i.e., $\theta = 0.25$ in the left panel and $\alpha_{US} = 0.62$ in the right panel). The other lines are obtained by varying θ (left panel) or α (right panel), while keeping the rest of the parameters at their U.S. values.

Identifying ξ and μ_M. As ξ affects firms' demand for outside managers relative to production workers, it is mainly identified from the aggregate managerial employment shares reported in Table 2. More specifically, by using (13) and (23), the model implies that the aggregate demand for managerial workers is given by

$$M^{\frac{\vartheta-1}{\vartheta}} = \xi^{\frac{\sigma}{1-\sigma}} \frac{1}{\mu_M} \left(\frac{\sigma}{\omega_M}\right)^{1/(1-\sigma)} \times \sum_{n \geq n^*(\xi)}^{\infty} n\varphi_n - \frac{T}{\mu_M \xi} \sum_{n \geq n^*(\xi)}^{\infty} \varphi_n, \tag{30}$$

where M is the share of outside managers, $\omega_M = \frac{w_M}{Y}$ is the normalized managerial wage, n^* is the delegation cutoff, which depends on ξ [see (9)] - and $\varphi_n = F^H \nu_n^H + F^L \nu_n^L$ is the total mass of firms with n products according to the endogenous firm size distribution as described in Proposition 1. Hence, holding φ_n and ω_M constant, the share of the workforce employed in managerial occupations is increasing in ξ.[21] The lower share of outside managers in India therefore implies - all else equal - that $\xi_{IND} < \xi_{US}$. Note also that (30) illustrates why it is important to introduce other mechanisms that affect the firm size distribution in India: For a given level of delegation benefit ξ, any shift in the distribution of firm size *towards* larger firms (due to an increase in θ, for instance) will increase managerial demand.[22]

To separately identify the efficiency of delegation ξ from the supply of managerial skills μ_M,

[21] Note that n^* is decreasing in ξ.

[22] Formally, the right-hand side of (30) can be written as $\frac{T}{\mu_M \xi} \times \sum_{n \geq n^*}^{\infty} \left(\frac{1}{n^*} - \frac{1}{n}\right) \varphi_n$, so that a reallocation of market share towards large firms increases managerial demand.

we adopt the following procedure.[23] By choice of units for managerial skills, all allocations in the model only depend on $\mu_M \times \xi$. To induce variation in the demand for managerial skills holding managerial human capital fixed, we use data from the New Immigrant Survey (NIS), which contains information about the pre- and post-migration outcomes of recent immigrants to the U.S. and has recently been used by Hendricks and Schoellman (2016). In particular, suppose that managerial skills in the population of Indian migrants to the U.S. are pareto distributed with shape ϑ and mean $\hat{\mu}_M^{IND}$. This structure implies that if Indian immigrants are positively selected with respect to their managerial skills, we should have $\hat{\mu}_M^{IND} > \mu_M^{IND}$. Letting λ_c denote the managerial employment shares in country c (which is reported in Table 2) and λ_c^M the managerial share of Indian immigrants in country c, the Pareto distribution implies that

$$\lambda_c = \tilde{\vartheta}\left(\omega_M^c\right)^{\vartheta}\mu_{M,c}^{\vartheta} \quad \text{and} \quad \lambda_c^M = \tilde{\vartheta}\left(\omega_M^c\right)^{\vartheta}\left(\hat{\mu}_M^{IND}\right)^{\vartheta},$$

where ω_M^c is the relative managerial wage in country c and $\tilde{\vartheta}$ is a constant. The average managerial human capital in India relative to the U.S. can therefore be identified from

$$\frac{\mu_{M,IND}}{\mu_{M,US}} = \underbrace{\left(\frac{\lambda_{US}^M}{\lambda_{US}}\right)^{1/\vartheta}}_{\text{uncorrected ratio}} \times \underbrace{\left(\frac{\lambda_{IND}}{\lambda_{IND}^M}\right)^{1/\vartheta}}_{\text{selection correction term}}. \tag{31}$$

The first term in (31) compares migrants and U.S. natives in the U.S. economy, i.e., holding ξ constant. Differences in managerial employment are therefore interpreted as differences in human capital. The second term accounts for selection into migration: if immigrants are positively selected on their managerial skills (as empirically shown in Table 5 below), i.e., $\lambda_{IND}^M > \lambda_{IND}$, the observed differences in outcomes in the U.S. *under*estimate the differences in skills in the population.[24] The last term in equation (31) corrects for that potential selection.

Identifying $\theta_E, \vartheta, \sigma, T$, and γ. The efficiency of the entry technology θ_E is identified from the aggregate entry rate. The shape parameter of the managerial skill distribution ϑ can be directly calibrated to match the dispersion in managerial earnings.[25] As σ is the elasticity of profits with respect to managerial services, we identify it from the share of managerial compensation relative to corporate profits. The owner's time endowment T is directly related to the need of managerial delegation and hence determines both the extensive margin of managerial hiring, i.e., the share of firms who hire outside managers, and the entrepreneurial profit share. The innovation step-size γ, translates firms' innovation outcomes into aggregate growth (see Lemma 1). As γ does not

[23] See Section B.3 in the Appendix, where we discuss this in more detail.

[24] We want to note that this identification relies on there not being excessive frictions to enter managerial positions (relative to other jobs) for Indians in the U.S. If immigrants from India do not enter managerial occupations because they are discriminated against, we would conclude that they have relatively little human capital. See also Hsieh et al. (2013) for an elaboration of this point.

[25] In fact the model implies that the variance of log managerial earnings is given by ϑ^{-2}.

enter any other moment in the model, we can simply choose γ to exactly match the aggregate growth rate.

Identifying ζ and ρ. As we do not have data on spending on innovation, we do not attempt to estimate the curvature of the expansion cost function, ζ. Instead we follow the microeconomic literature on $R\&D$ spending, whose estimates imply a quadratic cost function, i.e., $\zeta = 0.5$.[26] We come back to this restriction in Section 5, when we discuss the robustness of our results. Lastly, we set the discount rate ρ equal to 2%, which roughly corresponds to an annual discount factor of 97%.

4.2 Calibration Results

The results of our calibration are contained in Tables 3 and 4. In Table 3 we report the moments - both for the model and the data. Table 4 contains the calibrated parameters. There we also report the main target for the respective parameters even though the parameters are calibrated jointly.

We first start with the U.S. calibration results. As seen in the first two columns of Table 3, the model is able to rationalize most empirical moments. In particular, it matches the observed life cycle, i.e., average employment for 21-25 year old firms (relative to 1-5 year old firms), the differences in exit rates, whereby small young firms are around 1.5 times as likely to exit as small old firms[27] and the aggregate share of managerial workers reported in Table 2. The model underestimates the aggregate employment share of old firms and the share of firms without any outside managers.[28]

This is similar for the calibration to the Indian economy. In contrast to the U.S. case, we do not explicitly target the share of managerial compensation, as the Indian data for informal firms in the NSS does not provide information on managerial compensation. Hence, we keep σ constant at its respective U.S.[29] We also do not recalibrate the dispersion of (relative) managerial ability, because our identification strategy for Indian migrants relies on ϑ being the same across countries [see equation (31)]. Note that this restriction is not very important as empirically the cross-sectional dispersion in managerial wages is very similar across the two countries (0.49 in the U.S. vs. 0.45 in India). All remaining parameters are recalibrated. The model is again able

[26] See Akcigit and Kerr (2017) and Acemoglu et al. (2013), who discuss this evidence in more detail.

[27] In particular, while young plants (i.e., plants of age 1-5) with 1-4 employees have an exit rate of 21% per year, 21-25 year old plants of an equal size have an exit rate of only 14%.

[28] One reason why the model predicts slightly too few old firms is that in our model growth is only driven by the extensive margin of adding products. Hence, the process of growth and the resulting exit hazard are tightly linked. If we allowed for growth on the intensive margin [e.g., through quality innovations within existing product lines as in Akcigit and Kerr (2017) or Garcia-Macia et al. (2015)], we could break this link. As for the share of firms without any managerial personnel, our calibration implies that the delegation cutoff in the U.S., n^*, is smaller than unity.

[29] The model implies this moment to be 5.5% for India. To get a sense of whether this is the right order of magnitude, note that it is arguably the firms in the ASI that mostly hire managerial personnel. For these firms, managerial compensation amounts to 18% of the aggregate profits. As the firms in the ASI account for roughly 25% of employment, the implied moment in India would be about $18\% \times 25\% = 4.5\%$ if the aggregate profits and employment were in the same proportion in the ASI and the NSS.

Table 3: Moments for the U.S. and India

		U.S.		*India*	
		Data	Model	Data	Model
M1.	Employment share of 21-25-year-old firms (%)	8.10	6.01	7.70	6.00
M2.	Relative exit rate of small 21-25-year-old firms	1.50	1.51	1.10	1.10
M3.	Aggregate growth rate (%)	1.70	1.70	2.60	2.60
M4.	Mean employment of 21-25-year-old firms	2.55	2.55	1.12	1.12
M5.	Share of managers in workforce (%)	12.4	12.4	1.70	1.69
M6.	Variance of log manager wage	0.49	0.49	n/a	n/a
M7.	Entry rate (%)	7.30	7.23	7.00	6.90
M8.	Share of entrepreneurial profit (%)	21.0	21.0	48.3	48.3
M9.	Share of manager compensation (%)	51.0	54.6	n/a	n/a
M10.	Employment share of no-manager firms (%)	5.00	0.00	77.0	80.1
M11.	Relative managerial share of Indian migrants	n/a	n/a	2.11	2.11

Notes: Table reports both the data moments and the corresponding moments in the model for the U.S. and India. The average size of 21-25 year old plants relative to 1-5 year old plants, the entry rate and the aggregate employment share of 21-25 year old plants is directly calculated from the BDS (for the U.S.) and the ASI/NSS (for India). The relative exit rate of small 21-25 year old firms in the U.S. is the exit rate of 21-25 year old plants with 1-4 employees relative to the exit rate of 1-5 year old plants of equal size, which we also calculate from the BDS. The Indian micro data does not have a panel dimension. Hence, we follow Hsieh and Klenow (2014) to calculate exit rates from the relative size of cohorts across different census years. This does not allow us to calculate exit rates conditional on size. Hence, for the case of India, we take the unconditional exit rates (To the extent that old firms are larger than young firms and the exit hazard is declining in size, this represents an upper bound for the age difference in the conditional exit probability.). The aggregate managerial employment share and the variance of log managerial wages are calculated from IPUMS [see also Table 2]. The variance of log managerial wages is constructed from residual wages, after controlling for sector fixed effects. The relative managerial share of Indian migrants is calculated as $(\lambda_{US}^{M}/\lambda_{IND}^{M})$, where λ_{c}^{M} is the managerial share of Indian migrants in country c. The share of entrepreneurial profits relative to aggregate income for the U.S. (21%) is taken from Buera et al. (2011), the corresponding value for India is calculated from Indian micro data. The share of managerial compensation, i.e., managerial payments relative to corporate profits gross of managerial payments, is calculated from NIPA. The rate of aggregate growth refers to the average growth rate of TFP between 1970 and 2005 according to the Penn World Tables. See Section B.1 in the Appendix for details. "n/a" implies that the moment is not targeted in the calibration for the corresponding country.

to match the data well. It replicates the essentially flat life-cycle of Indian plants, the low share of aggregate managerial employment and the fact that, in contrast to the U.S., young plants exit almost at the same rate as old plants.[30] As is the case for the U.S. calibration, the model underestimates the share of old firms in the economy.[31] Note also that firms in India have a much higher share of entrepreneurial profits. This is due to the fact that most firms in India are small so that most of their sales are attributed as entrepreneurial compensation for the provision of the fixed factor T.

[30] This result is consistent with the one reported in Hsieh and Klenow (2014), see Figure 2.

[31] At first glance it might be surprising that old firms, i.e., firms of ages 21-25, have roughly the same aggregate employment share in the U.S. and India. The reason is that the aggregate employment share of *very* old firms is much higher in the U.S. In the U.S. (India) the share of firms older than 25 years is 55% (20%). See Sections OA-2.1 and OA-2.2 in the Online Appendix for details.

Table 4: Parameters for the U.S. and India

Parameter	Interpretation	Target	U.S.	India
	Panel A. Internal Calibration			
θ	Innovativeness of incumbents	Life-cycle	0.250	0.053
α	Share of high type	Age vs exit profile	0.621	0.128
ξ	Delegation efficiency	Managerial employment share	0.477	0.240
μ_M	Average managerial skill	Immigration data (Equation 31)	$1.000^{\dagger}$	0.420
β	Relative creative destruction	Empl. share of old firms	5.748	2.363
θ_E	Innovativeness of Entrants	Rate of entry	0.119	0.107
ϑ	Pareto shape	Var of Log manager wage	1.429	1.429^{*}
σ	Curvature of efficiency	Managerial compensation	0.619	0.619^{*}
T	Managerial endowment	Share of non-managerial firms	0.103	0.340
γ	Innovation step size	Aggregate growth rate	1.140	1.463
	Panel B. External Calibration			
ζ	Curvature of the expansion cost function		0.50	0.50
ρ	Discount rate		0.02	0.02

Notes: Table reports the parameter values that yield the model moments reported in Table 3. We denote normalized parameters by "†" and parameters which we do not calibrate to by "*".

In Table 4 we report the corresponding structural parameters. The first two rows show that entrants in the U.S. economy are much more likely to be high-type firms, $\alpha_{US} > \alpha_{IND}$, and that such firms are vastly more efficient in expanding - in particular, $\theta_{US} \approx 5 \times \theta_{IND}$, i.e., innovative firms in the U.S. are estimated to be 5 times as efficient in expanding into new markets as their Indian counterparts. Additionally, we estimate that $\beta > 1$, which implies that low-type firms are subject to relatively higher probabilities of creative destruction and that this asymmetry is more pronounced in the U.S. Empirically, these differences reflect mostly the observed differences in life-cycle growth and exit patterns. Economically, we find these estimates plausible in that they capture the above-mentioned additional reasons for why firms in India might not expand (e.g., due to the presence of credit constraints) or why unproductive firms are abundant upon entry (e.g., because of low opportunity costs of entrepreneurship in India).

The next two rows contain the estimates of the delegation environment. In particular, our calibration implies that the delegation efficiency in the U.S. is about twice as large as in India ($\xi_{US} \approx 2 \times \xi_{IND}$) and that the U.S. labor force has a comparative advantage in managerial occupations ($\mu_{M,US} > \mu_{M,IND}$). The latter is identified from the fact that Indian immigrants in the U.S. are almost as likely to work as managers as the native U.S. population but that they are *more* likely to work as managers prior to migrating *compared* to the Indian population. This is seen in Table 5, where we show that Indian migrants to the U.S. were almost four times as likely to have worked as managers in India. According to equation (31), this leads us to infer that the unselected population in India has a comparative disadvantage in managerial occupations relative to the population in the U.S.. The higher delegation efficiency in the U.S. is then inferred from the low share of outside managers in India after taking the low managerial human capital into account.[32]

Table 5: Identification of managerial skills: Managerial Employment Shares

	U.S.		India	
	U.S. population λ_{US}	Indian migrants λ_{US}^{M}	Indian population λ_{IND}	Indian migrants λ_{IND}^{M}
Managerial share	12.4 %	12.9 %	1.7%	6.1%

Notes The table contains estimates for the managerial employment share in the native population of the U.S. (column 1), the population Indian immigrants in the U.S. (column 2), the native population in India (column 3) and the sample of Indian migrants to the U.S. *in* India (column 4). For the definition of outsider managers, see Table 2 and the discussion there. λ_{US} and λ_{US}^{M} are calculated from the U.S. census and λ_{IND} from the Indian census. λ_{IND}^{M} is calculated from the data of the New Immigration Study. We refer to Hendricks and Schoellman (2016) for a detailed description of the data. For the New Immigration Study we use the occupational codes "10 to 430: executive, administrative and managerial" and "500 to 950: management related" as referring to managers. We also insist on the individual having received a salary (instead of for example being self-employed).

Again we want to stress that our estimate of ξ_{IND} is *conditional* on other determinants of firm size induced by differences in for example θ, α, or θ_E. The reason why such other mechanisms are not able to explain *both* the differences in firm dynamics and managerial hiring simultaneously is the general equilibrium adjustment of relative wages. Precisely because the cost of expansion and the share of subsistence firms are high in India, there are few large firms in the Indian economy. To clear the labor market, managerial wages fall. In our calibration, this decrease in wages is sufficiently large (despite the substitutability between workers and managers) that a lower delegation efficiency ξ is required to explain the lack in managerial hiring. Another way to see this is the following: Suppose we kept the main parameters of the delegation margin, ξ and μ_M, at the U.S. level, but recalibrated the remaining parameters of the model to match all the Indian moments in Table 3 *except* the managerial employment share and relative employment patterns of Indian immigrants. While the model is again able to match the firm-level data moments equally well, the resulting equilibrium share of outside managers is 13.1%, which is way above the Indian level and even higher than the U.S. level. Hence the model requires a low delegation efficiency $\xi_{IND} < \xi_{US}$ to explain the lack of managerial hiring in India.

4.3 Results: Firm Dynamics and Delegation in the U.S. and India

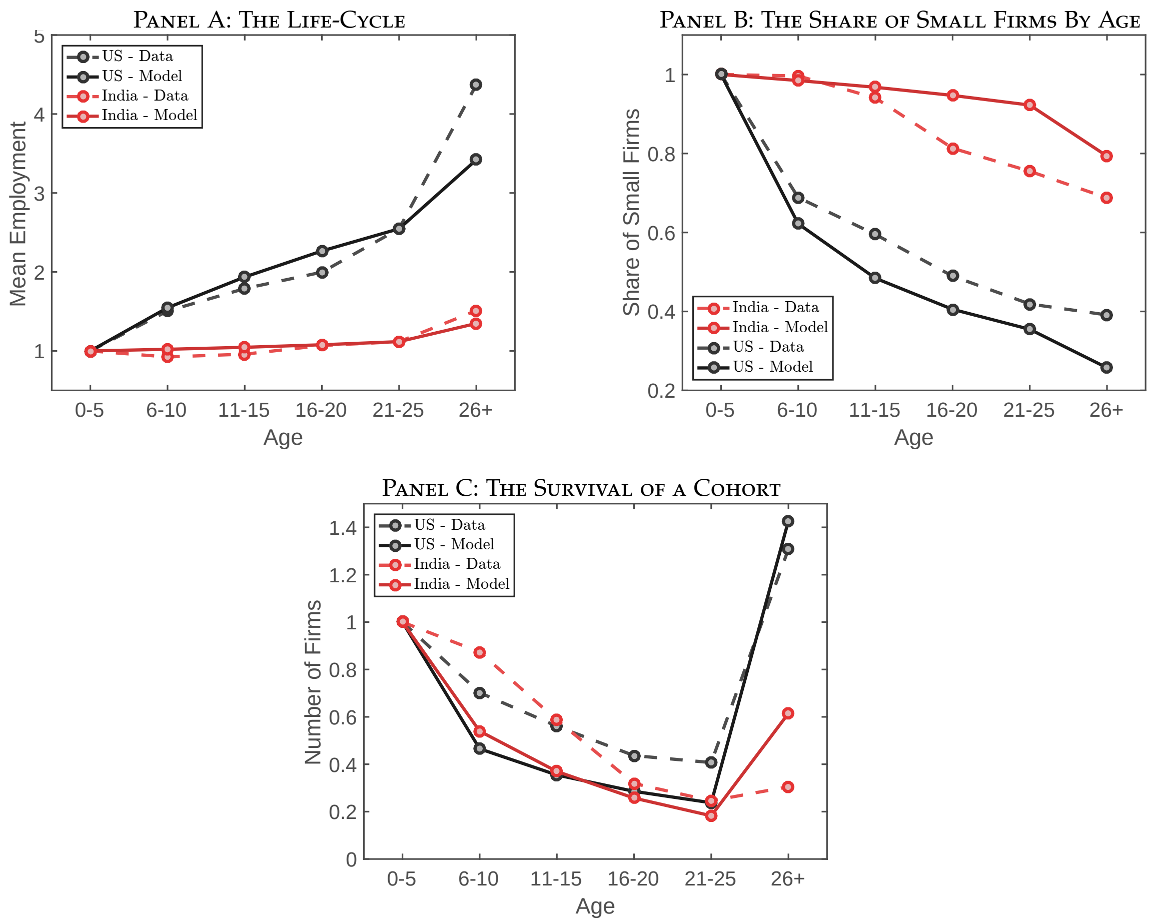
4.3.1 Lack of Selection in India

With the calibrated models at hand, we can now give a more structural interpretation to the differences in firm dynamics in the U.S. and India. The process of firm dynamics is fully sum-

[32] Note also that the step-size of innovation is calibrated to be higher in India ($\gamma_{IND} > \gamma_{US}$) as the Indian economy will endogenously have less creative destruction but a slightly higher rate of productivity growth. Recall that γ does not affect the process of firm dynamics in our model.

marized by the joint distribution of age and size. In Figure 5 we display different aspects of this distribution - both in the data and in the calibrated model.

Figure 5: Firm Dynamics in the U.S. and India



Notes: The figure displays three aspects of the process of firm dynamics both for the data (solid lines) and the model (dashed lines). Panel A depicts the cross-sectional age-size relationship, i.e., average plant employment as a function of age. Panel B depicts shows the share of small firms by age. For the U.S. we define small firms as all plants with 1-4 employees (which is the smallest size category). For India we define small firms as all plants with a single hired employee. In the model we look at firms that are active in a single market. Panel C depicts the share of firms by age relative to the share of firms in the youngest age category. The data for the U.S. correspond to the population of U.S. manufacturing plants in 2012 and derive from the BDS. The data for India correspond to the Indian manufacturing plants in 2010 and are taken from the ASI and the NSS. The parameters are contained in Table 4.

Panel A shows the employment life-cycle, i.e., average size by age, Panel B shows the share of small firms by age (relative to their share among young firms), and Panel C shows the extent of survival, i.e., the size of the cohort (relative to the entering cohort) by age. Even though the model is calibrated to match only one number in Panel A for the life-cycle and the aggregate employment share by age,[33] Figure 5 shows that the model replicates the salient features of the differences in firm dynamics between the U.S. and India well. In particular, Panel B matches an important (and not explicitly targeted) by-product of the flat life-cycle in India: The average old firm in India is small because there are still ample tiny old producers. In particular, while the share of small firms in the U.S. declines to 40% by the age of 25, the vast majority of old firms in India still only produces a single variety.[34]

Our theory stresses the importance of creative destruction and selection, i.e., the process by which some firms systematically grow at a faster rate and replace other, stagnant producers, in shaping this process of firm dynamics. In our calibrated model, the extent of aggregate creative destruction τ is almost twice as large in the U.S. as in India. Figure 5 shows which patterns in the data lead our model to infer this to be the case. Consider Panel C, which shows the survival of a cohort, i.e., the number of firms by age *relative* to the number of entering firms. The extent to which firms manage to survive as they age is reasonably similar in the U.S. and in India - both in the data and in the model.[35] At first glance it seems surprising how the extent of exit by age can be similar in these economies, despite the sizable difference in creative destruction. The answer is contained in the remaining panels of Figure 5. Recall that the number of exiting firms is the *product* of the mass of firms operating in a single market and the rate of creative destruction. Even though the latter is much higher in the U.S., there are also fewer small firms. Intuitively, while a large share of creative destruction in India results in a firm-exit, most creative destruction in the U.S. takes place in inframarginal markets, where firms lose market share without exiting. The fact that both the aggregate exit rate and the exit rates by age are of a similar magnitude, *despite* the fact that many old firms in India are close to the exit threshold, implies that there is much more creative destruction in the U.S.

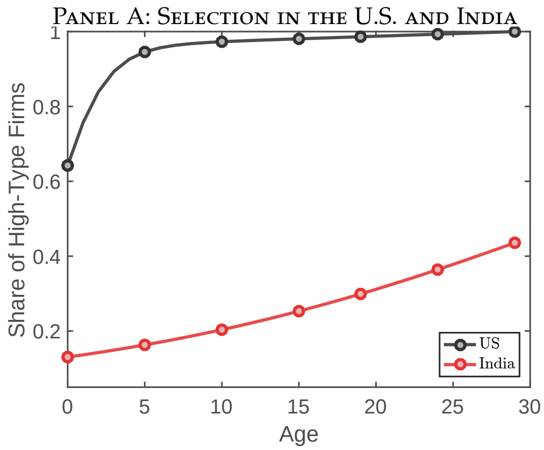
Through the lens of our model, we can also study the implications of these patterns of firm growth and exit contained in Figure 5 on the extent of endogenous selection. In Panel A of Figure 6 we display the share of high-type firms within a cohort. Two results stand out. First of all, the share of high-type firms in the U.S. is significantly bigger among the entering cohort as ($\alpha_{US} = 0.62$ and $\alpha_{IND} = 0.13$). Second, high-type firms grow faster in the U.S., creating a much stronger selection force. While the share of high-type firms of age 20+ is essentially 100% in the U.S., high-type firms are still in the minority among old plants in India: even for 30-year-old plants, more than half of them are low-type firms in India.

[33] More specifically, we directly target both the life-cycle and the aggregate employment share for firms of age 21-25 (see Table 3).

[34] In the U.S. data, we only see the number of firms for different employment bins. The smallest employment category corresponds to 1-4 employees, which we therefore take as our definition of small firms in the U.S. In India, we see the entire micro data and hence we define small firms to be firms with a single employee. In the model they correspond to one-product firms.

[35] As for the category of 26+ firms: Note that this is the *accumulated* stock of surviving firms, who are older than 26 years. Hence, even though the U.S. exit rates are only slightly lower than in India, the small differences in the flow of exit add up to a sizable difference in the stock of old firms. See also Figure 2 and 3 in Hsieh and Klenow (2014), who also show that exit rates are only slightly lower in the U.S. but that the aggregate employment share of old firms (i.e., the product of Panels A and C in Figure 5) is vastly larger in the U.S.

Figure 6: Endogenous Selection



Notes: Panel A shows the share of high-type firms by age both for the India calibration (red line) and for the U.S. calibration (black line). Panel B shows the counterfactual share of high-type firms by age if the initial share of high-type firms in a cohort in the U.S. (India) was given by its Indian (US) counterpart α_{IND} (α_{US}). For comparison we also display the calibrated share of high-type firms contained in Panel A in dashed lines. All calibrated parameters are taken from Table 4.

How much of this lack of selection is due to the fact that there are simply very few high-type firms in India to begin with? The answer to this question is depicted in Panel B. There we simulate a *counterfactual* cohort of U.S. firms, which starts with the initial type distribution of India, i.e., where the initial share of high-type firms was α_{IND} (illustrated by the solid black line). It is clearly seen that the differences in growth incentives of existing high-type firms in the U.S. and India are a key aspect of the selection dynamics: by the age of 20, this cohort would again be populated only by high-type firms despite the high share of subsistence entrepreneurs at the time of entry. Conversely, even if a cohort in the Indian economy were to start with α_{US} high-type firms (the solid red line in Figure 6, Panel B), the process of selection would be very slow and a substantial share of stagnant producers would be able to survive.

Figures 5 and 6 summarize why the majority of firms in India are small but still experience survival rates similar to the U.S. First of all, the vast majority of firms in India (around 90% in our calibration) are subsistence entrepreneurs upon entry, which are not destined to grow in the first place. That they do not exit despite being perilously close to the exit threshold is due to a lack of creative destruction: even the firms that can grow are quite inefficient in doing so, which in turn allows stagnant firms to survive. This view of the world, through the lens of our model, has the important implication that size-based policies that favor small firms could easily be detrimental. In particular, policies targeted at small producers could very well support stagnant subsistence firms instead of helping firms which, for example, face credit constraints or other frictions to expand. In this sense, our calibrated model of firm dynamics complements the recent findings of Hsieh and Olken (2014). In their empirical analysis of micro data for the population of firms in

Mexico, Indonesia and India, these authors argue that "the problem of economic development in low-income and middle-income countries is how to relieve the differential constraints faced by large firms, not how to relax the constraints faced by small firms. Indeed, this view suggests that programs such as microcredit or simplified tax regimes that benefit only small firms may worsen the development problem." This is very consistent with the findings of our analysis.

4.3.2 Firm Dynamics and the Delegation Efficiency ξ

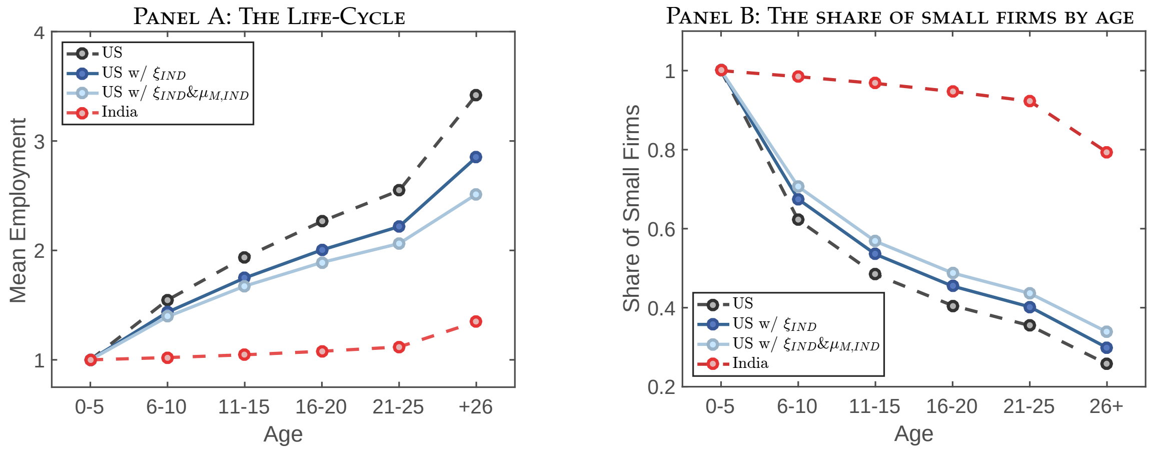
How important are the differences in the delegation efficiencies, ξ_{US} vs ξ_{IND}, to explain the differences in firm dynamics displayed in Figure 5? To answer this question, we start by considering the behavior of U.S. firms if they were subject to the Indian level of delegation efficiency, ξ_{IND}. We are particularly interested to analyze the resulting change in life-cycle growth and the extent to which a less developed system of delegation allows small firms to survive by shielding them from creative destruction. We will then also consider the alternative strategy of considering the performance of Indian firms, when we improve the prevailing delegation efficiency to the U.S. level. These exercises will give different answers to the extent that the delegation efficiency ξ and other aspect of the economy, such as the expansion efficiency θ or the share of high-type firms α, are complements. It turns out that this is very much the case in our setting.

The Impact of Delegation Efficiency ξ in the U.S. We first focus on the U.S. and lower the efficiency of delegation from ξ_{US} to the level in India (ξ_{IND}). Consider first Figure 7, where we depict the implications on the extent of life-cycle growth and the share of small firms by age.[36] For both outcomes, we depict the U.S. and India calibration in black and red and the partial effect of only changing the delegation efficiency in the U.S. to the Indian level in dark blue.

Focusing first on the life-cycle in the left panel, we see that limits to delegation reduce firms' growth incentives. While firms in the U.S. are about 2.55 times larger than new entrants, they would only be 2.2 times larger, if delegation efficiency was at the level of India. Given that Indian firms hardly grow at all as they age, differences in the delegation efficiency can plausibly account for about 20-25% of the observed differences in life-cycle growth between the U.S and India. Similarly, the higher delegation efficiency in the U.S. also contributes to the steeper decline in the share of small firms by age as depicted in Panel B. If U.S. firms had only access to the delegation efficiency in India, the share of small firms among firms of age 21-25 would increase by five percentage points from 35% to 40%. This amounts to around 10% of the difference between the U.S. and India. Hence, the ability of U.S. firms to efficiently procure managerial services from outside managers is a quantitatively important determinant of the process of firm dynamics in the U.S. Table 6 reports these numbers for different cohorts.

[36] As we argued above, the distribution of age depicted in Panel C in Figure 5 is not particularly informative about the degree of selection and creative destruction and is therefore not materially affected by changes in the delegation efficiency. Results are available upon request.

Figure 7: Firm Dynamics and Delegation Efficiency in the U.S.



Notes: The figure depicts the implications of reducing the efficiency of delegation from ξ_{US} to ξ_{IND}. In Panel A we depict the life-cycle of plants, in Panel B we depict the share of small firms, i.e., firms that produce in a single market, by age. For both outcomes we depict that the calibrated U.S. economy (black line), the calibrated Indian economy (red line), the U.S. economy with the Indian delegation efficiency ξ_{IND} (dark blue line), and the U.S. economy with both the Indian delegation efficiency ξ_{IND} and the level of managerial human capital in India, μ_{IND} (light blue line). All remaining parameters are from Table 4.

Table 6: U.S. Firms with Indian Delegation Environment

	Life-cycle growth			Share of small firms		
	11-15	21-25	26+	11-15	21-25	26+
U.S. firms with ξ_{IND}	21.1%	23.0%	27.4%	10.6%	8.3%	7.7%
U.S. firms with ξ_{IND} and $\mu_{M,IND}$	29.5%	33.9%	43.7%	17.3%	14.4%	15.1%

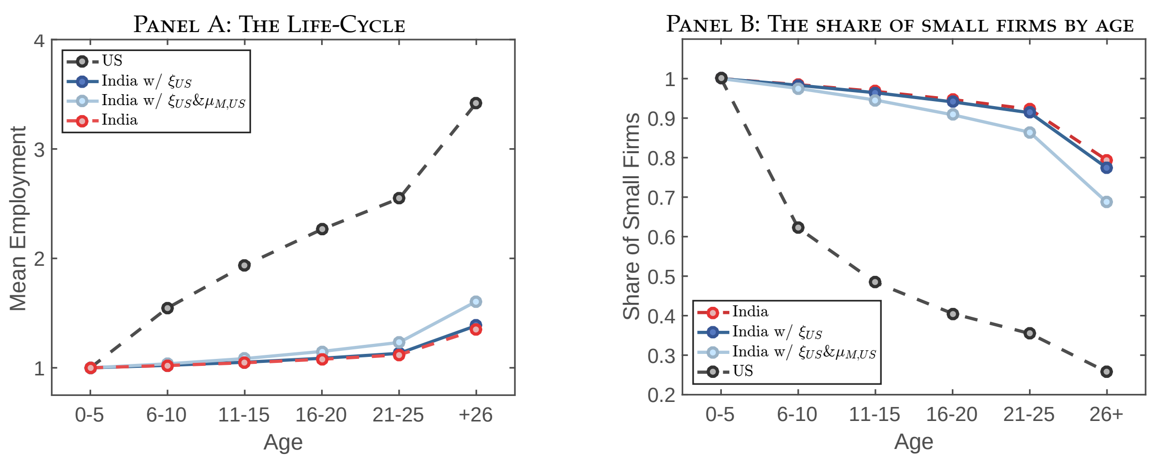
Notes: The table reports - for the each age group - the share of the differences in life-cycle growth and the share of small producers between U.S. and India that can be explained by the differences in delegation efficiency ξ and managerial human capital μ_M. The first row presents the case for U.S. firms if their delegation efficiency was ξ_{IND}. The second row shows the combined effect of reducing ξ and μ_M to their Indian levels.

As discussed above, the equilibrium allocations in the model depend on $\xi \times \mu_M$ jointly, i.e., the product of delegation efficiency (ξ) and managerial human capital (μ_M). The information contained in the immigration data is therefore used only to *decompose* $\xi \times \mu_M$ into the supply of managerial human capital μ_M and the demand for managerial services ξ. For completeness we therefore also display the *total effect* of the delegation environment, i.e., the difference resulting from $\xi \times \mu_M$ being higher in the U.S., in Figure 7 in light blue. Because our estimates imply that $\mu_M^{US} > \mu_M^{IND}$, the implications are larger. More specifically, the cross-country difference in this joint effect explains 34% of the observed life-cycle difference for the 21-25 year-old firms. As this would be the effect of delegation efficiency in a world, which abstracts from differences in managerial human capital, we view this as an upper bound for the direct effect of the efficiency of delegation.

The Impact of Delegation Efficiency ξ in India Figure 7 showed that the higher delegation efficiency in the U.S. partly explains why surviving firms in the U.S. are large and why few old firms are small. Similarly we can also ask whether the low delegation efficiency in India is an important contributor for Indian firms being small. The difference between these two decompositions is informative about complementarities between the ease of delegation and other aspects of the economy. Intuitively, seamless delegation is probably of greater importance for the aggregate economy if dynamic firms are plentiful and their expansion technology is efficient. This is exactly what we find.

Figure 8, which mimics the structure of Figure 7, depicts the resulting patterns of firm dynamics if Indian firms had access to the U.S. level of delegation efficiency. Likewise, Table 7 repeats the decomposition of Table 6 for India. We see that the quantitative effects of an improvement in delegation efficiency are much more muted. While the rate of life-cycle growth for Indian firms would increase if the delegation environment were to improve, the effect is substantially smaller. In particular, the average size of 21-25-year-old firms (relative to new entrants) would increase only from 1.12 to 1.14. Similarly, the share of small firms aged 21-25 would hardly decrease. In Figure 7 we also depict the total effect of the delegation environment, ξ and μ_M. As expected, the effect is slightly larger (1.25), but still quantitatively small.

Figure 8: Firm Dynamics and Delegation Efficiency in India



Notes: The figure depicts the implications of increasing the efficiency of delegation from ξ_{IND} to ξ_{US}. In Panel A we depict the life-cycle of plants, in Panel B we depict the share of small firms, i.e., firms who produce in a single market, by age. For both outcomes we depict that calibrated U.S. economy (black line), the calibrated Indian economy (red line), the Indian economy with the U.S. delegation efficiency ξ_{US} (dark blue line), and the Indian economy with both the U.S. delegation efficiency ξ_{US} and the level of managerial human capital in the U.S., μ_{US} (light blue line). All remaining parameters are from Table 4.

The differences between Figures 7 and 8 highlight the importance of complementarities between the delegation environment and other determinants of firm dynamics. In the U.S. economy, high-type firms are abundant and the cost of innovation is low (i.e., α_{US} and θ_{US} are high).

Preventing these dynamic entrepreneurs from growing by subjecting them to the inefficient delegation environment of India is costly in terms of life-cycle growth and reduces the extent of selection substantially. In contrast, in India transformative entrepreneurs are not only relatively scarce but they also expand less efficiently (i.e., α_{IND} and θ_{IND} are low). While there is a benefit to allowing these firms to sustain their expansion incentives through better delegation, the aggregate effects are much smaller.[37]

Table 7: Indian Firms with U.S. Delegation Environment

	Life-cycle growth			Share of small firms		
	11-15	21-25	26+	11-15	21-25	26+
Indian firms with ξ_{US}	0.5%	1.2%	1.8%	0.7%	1.6%	3.7%
Indian firms with ξ_{US} and $\mu_{M,US}$	4.3%	9.0%	12.5%	4.5%	10.3%	19.9%

Notes: The table reports - for the each age group - the share of the differences in life-cycle growth and the share of small producers between U.S. and India that can be explained by the differences in delegation efficiency ξ and managerial human capital μ_M. The first row presents the case for Indian firms if their delegation efficiency was ξ_{US}. The second row shows the combined effect of increasing ξ and μ_M to their U.S. levels.

Steady-state Implications of the Model Figures 7 and 8 report the implications of differences in ξ for the patterns of firm growth and exit by age. In Table 8 we report the implications on the stationary distribution. In columns 1 and 2 we report the results for the calibrated economy in the U.S. and India. As suggested by Figure 6, high-type firms are of limited importance for the Indian economy. In the stationary distribution in the U.S., around 96% of firms are high-type firms (compared to 62% at the time of entry) and they have a combined market share of 98% as they are bigger on average. In India, high-type firms account for only 31% of firms and 38% of aggregate employment. These missing expansion incentives for high-type firms in India allow low-type firms to survive, thereby shifting the Indian firm size distribution to the left, causing a plethora of small firms. Not only do firms with a single product employ 80% of the workforce and the average firm is only one third as large as in the U.S., but none of these single-product firms employ any managers, as the returns to delegation are low. This is very different in the U.S. Firms with a single product account for only a small share of economic activity and the high efficiency of outside managers in the U.S. also implies that all firms in the U.S. rely on outside managers to provide managerial services.The equilibrium summary statistic for these dynamic properties is the rate of creative destruction, which is also lower by almost 50% in India relative to the U.S.

Columns 3 and 4 show the extent to which these differences are driven by differences in delegation efficiency. Consider first the case of the U.S. contained in column 3. If delegation in

[37] Relatedly, we also want to note that the counterfactual equilibrium managerial shares are quite different. If we endow the U.S. economy with India's delegation efficiency ξ_{IND}, the implied equilibrium managerial share declines from 12.4% to 5.2%, which is in the same ballpark than India's actual share of 1.7%. If on the other hand, Indian firms could hire managers at the U.S. level of efficiency ξ_{US}, managerial employment would only increase to 4.5%.

the U.S. was as unproductive as in India, the employment share of small firms would increase and average firm size would decline by roughly 15%. Furthermore, the extent of creative destruction would decrease by 25%, which is half of the gap between the U.S. and India. Note that these qualitatively large effects are present despite their being only small effects on the long-run share of high-type firms. The reason is that - as seen in Figure 6 - low-type firms in the U.S. lose market share very quickly already. While a lower efficiency of delegation will prolong this process of shake-out, the long-run effects on the stationary distribution are modest. In column 4, we report the implications of the India experiment. While an improvement of delegation efficiency in India would increase average firm-size, reduce the importance of small producers and increase the degree of selection, the quantitative effects are more modest. Interestingly, this occurs *despite* the fact that outside managers do become significantly more productive and that Indian firms would in fact hire managers if the efficiency of delegation was at the U.S. level. However, given the remaining market environment, this increase in static profitability does not translate into very large differences in firm growth.

Table 8: Delegation Efficiency and the Steady State

	Calibrated Model		*Counterfactual Delegation Efficiency*	
	India	U.S.	U.S. w/ ξ_{IND}	India w/ ξ_{US}
Share of high-type firms	0.312	0.961	0.959	0.316
Employment share of high-type firms	0.375	0.987	0.984	0.383
Employment share by one-product firms	0.801	0.133	0.164	0.792
Employment share of firms without managers	0.801	0.000	0.000	0.000
Average firm size (rel to U.S.)	0.361	1.000	0.853	0.364
Aggregate innovation rate, τ	0.068	0.129	0.095	0.071

Notes: The table contains various equilibrium objects from the stationary distribution of the calibrated model. Columns 1 and 2 refer to the calibrated economies for the U.S. and India. Columns 3 and 4 contain the results for the U.S. (Indian) economy if the delegation efficiency was ξ_{IND} (ξ_{US}). The models are parametrized according to Panel B of Table 4.

5 Robustness

In this section, we study the robustness of our results, in particular the quantitative importance of changes in the delegation efficiency ξ on the process of firm dynamics. Above, we summarized these implications in Tables 6 and 7. Our main results suggest that the high delegation efficiency in the U.S. explains about 20-25% of the faster life-cycle growth and around 10% of the smaller importance of small firms (Table 6). For the case of India, the first row of Table 7 shows that the low delegation efficiency *alone* is not responsible for the slow life-cycle growth, precisely due to the complementarities. We are now going to discuss a variety of robustness checks, both with respect to the parameters we did not estimate and with respect to our calibration targets. In each exercise, we will report the results corresponding to the first rows of Tables 6 and 7, the share of the U.S.-India difference in (i) life-cycle growth and (ii) share of small firms that can be explained by the differences in delegation efficiency ξ.

5.1 Entry

In our benchmark specification, we assume that the entrants use the same form of innovation technology as incumbent firms, with curvature parameter $\zeta_e = 0.5$. In order to assess the importance of entrants for our results, we recalibrate our model, for both the U.S. and India, while setting ζ_e at various alternative values. The case of $\zeta_e = 0$ corresponds the case of exogenous entry. The higher the value of ζ_e, the more responsive are entrants to changes in the value of entry. Table 9 presents the results analogous to Tables 6 and 7. It suggests that as the entrants become more *responsive*, the effect of worsening (improving) the delegation environment for the U.S. (India) is dampened. Yet, the quantitative change compared to benchmark calibration is modest; even for a high value of ζ_e, the explained part of the differences in firm dynamics is around 18% for the case of the life-cycle growth and between 5% and 8% for the share of small firms.

Table 9: Entry Elasticity

	U.S. w/ ξ_{IND}						India w/ ξ_{US}					
	Life-cycle growth			Share of small firms			Life-cycle growth			Share of small firms		
	11-15	21-25	26+	11-15	21-25	26+	11-15	21-25	26+	11-15	21-25	26+
$\zeta_e = 0$	23.3%	25.9%	32.3%	12.3%	10.2%	10.4%	0.6%	1.0%	2.3%	0.7%	1.5%	4.2%
$\zeta_e = 0.2$	22.7%	25.1%	30.9%	11.8%	9.7%	9.6%	0.5%	1.0%	2.1%	0.7%	1.6%	4.0%
$\zeta_e = 0.8$	17.3%	18.0%	18.6%	7.7%	5.2%	3.2%	0.5%	1.0%	1.4%	0.7%	1.6%	3.1%

Notes: The table reports the results in Tables 6 and 7 for the case where the entry elasticity ζ_E takes different values. The remaining parameters are recalibrated.

5.2 Entrepreneurial Profits

In the data, Indian entrepreneurs have a significantly higher profit share compared to U.S. entrepreneurs (48% vs 21%). In our quantitative analysis, this difference manifests itself in a higher level of T in India. To see whether this feature of the data drives our main results, we recalibrate the model for India by targeting the U.S. value for the entrepreneurial profit share. As seen from Table 10, the resulting impact of the delegation efficiency ξ from our counterfactual exercises are essentially the same as the baseline results.

5.3 Exogenous Heterogeneity: α and β

As evident from the calibration results, we estimate striking differences in terms of the *types* of firms operating in the economy: India has a much higher share of subsistence producers upon entry ($\alpha_{IND} < \alpha_{US}$) and such low-type firms are subject to a lower creative destruction (relative

Table 10: Targeting U.S. Share of Entrepreneurial Profit for India

U.S. w/ ξ_{IND}						India w/ ξ_{US}					
Life-cycle growth			Share of small firms			Life-cycle growth			Share of small firms		
11-15	21-25	26+	11-15	21-25	26+	11-15	21-25	26+	11-15	21-25	26+
21.1%	22.9%	26.2%	10.8%	8.5%	7.4%	1.2%	1.8%	2.4%	1.5%	3.0%	5.2%

Notes: The table reports the results in Tables 6 and 7 for the case where we target an entrepreneurial share of 21% in India (instead of 48%). The remaining moments are given Table 3.

to high types) than their U.S. counterparts ($\beta_{IND} < \beta_{US}$). Although these differences are needed to explain the data well (through the lens of the model), one may wonder if these particular sources of heterogeneity are responsible for the results. To show that this is not the case, we recalibrated the model for the Indian economy while fixing α and β at their U.S. values and redid our counterfactual exercises. Table 11 shows that the importance of delegation efficiency remains strong for the U.S., with quantitatively very similar magnitude compared to baseline analysis.[38] On the other hand, for India, the effect of an increase in delegation efficiency on life-cycle growth and share of small firms is subdued, especially for old firms.

Table 11: Same α and β for U.S. and India

U.S. w/ ξ_{IND}						India w/ ξ_{US}					
Life-cycle growth			Share of small firms			Life-cycle growth			Share of small firms		
11-15	21-25	26+	11-15	21-25	26+	11-15	21-25	26+	11-15	21-25	26+
21.9%	23.1%	25.1%	11.4%	8.7%	6.7%	0.7%	0.6%	0.4%	0.9%	0.9%	0.8%

Notes: The table reports the results in Tables 6 and 7 for the case where we fix α and β in India at the U.S. level and recalibrate the remaining parameters.

5.4 Managerial Compensation

In the calibration, the elasticity of profits with respect to managerial services, σ, is identified mainly from the share of managerial compensation relative to corporate profits. We calculate this moment from NIPA between 2000 and 2007 and target the average value for our main analysis.[39] However, the precise value depends somewhat on the year used in the calculation. In Table 12 we show that targeting lower (40%) or higher (60%) shares of managerial compensation yields quantitatively similar results.

[38] Recall that we recalibrate ξ_{IND}. To the extent that our estimate for this parameter differs from the one reported in Table 4, the counterfactual U.S. life-cycle and share of small firms could be different.

[39] See Section B.1 in the Appendix for detailed information.

Table 12: Different Targets for Share of Managerial Compensation

	U.S. w/ ξ_{IND}						India w/ ξ_{US}					
	Life-cycle growth			Share of small firms			Life-cycle growth			Share of small firms		
	11-15	21-25	26+	11-15	21-25	26+	11-15	21-25	26+	11-15	21-25	26+
Low (40%)	20.2%	20.1%	20.2%	12.2%	8.7%	6.7%	1.0%	1.5%	2.1%	1.1%	2.2%	4.1%
High (60%)	23.6%	25.4%	28.5%	12.1%	9.5%	8.1%	1.0%	1.4%	1.5%	1.2%	2.1%	3.0%

Notes: The table reports the results in Tables 6 and 7 for the case where target different values for the share of managerial compensation. The remaining parameters are recalibrated to the moments reported in Table 3.

5.5 Incumbents' Innovation Production Function

As with our robustness exercise concerning entrants, we also study how the curvature parameter of the innovation production function for *incumbents*, ζ, affects our results. We consider two alternative values for ζ, which are in the ballpark of the lowest and highest micro estimates for this parameter[40]. Table 13, which summarizes the results, shows that a higher innovation *responsiveness* of incumbents to profit incentives leads to a stronger impact of a change in delegation efficiency. A lower ζ attenuates the importance of delegation on life cycle growth and the survival of small firms. Still, even for a more convex innovation cost function, life-cycle growth (the share of small firms) in the U.S. would decline by 17%-21% (increase by 6% - 9%) relative to India if the delegation efficiency was at the Indian level.

Table 13: Different Values for ζ

	U.S. w/ ξ_{IND}						India w/ ξ_{US}					
	Life-cycle growth			Share of small firms			Life-cycle growth			Share of small firms		
	11-15	21-25	26+	11-15	21-25	26+	11-15	21-25	26+	11-15	21-25	26+
$\zeta = 0.4$	17.2%	18.4%	21.0%	9.0%	6.8%	5.6%	0.5%	0.8%	1.2%	0.5%	1.1%	2.2%
$\zeta = 0.6$	26.1%	27.7%	30.7%	14.2%	11.2%	9.7%	0.8%	1.4%	2.4%	0.9%	1.9%	4.4%

Notes: The table reports the results in Tables 6 and 7 for the case where the elasticity of the innovation cost function is given by ζ. The remaining parameters are recalibrated to the moments reported in Table 3.

5.6 Firm-Level Analysis

In the main analysis, we have focused solely on plant-level data. We did so (i) to be consistent with the results reported in Hsieh and Klenow (2014) and (ii) to ensure comparability between the U.S. and India since we cannot link individual plants to specific firms in the Indian data. Here, we show that this choice has no substantial implications for our conclusions regarding the counterfactual implications of a change in the delegation efficiency. To show this, we recalibrate the model for the U.S. economy by focusing on firm-level moments and redo our main analysis.[41]

[40] For more on this, see Akcigit and Kerr (2017) and Acemoglu et al. (2013)

[41] Note that we do not repeat this robustness for India, as firm-level data is not available. With the majority of employment being accounted for by very small producers, multi-plant firms are unlikely to be important for the

The model is able to match the firm-level moments quite well.[42] The implied importance of the delegation margin is reported in Table 14. It suggests that, for the U.S., the explained fraction of the life-cycle growth differences based on firm-level data is slightly smaller than what we get from plant-level data. This is mainly driven by the fact that *observed* life-cycle growth difference between the U.S. and India at the firm level is greater than what is implied by the plant-level data. For India, the counterfactual results are essentially unchanged, because the estimate of ξ based on U.S. firm-level data is very close to the one based on plant-level data.

Table 14: Firm-Level Analysis for the U.S.

U.S. w/ ξ_{IND}						India w/ ξ_{US}					
Life-cycle growth			Share of small firms			Life-cycle growth			Share of small firms		
11-15	21-25	26+	11-15	21-25	26+	11-15	21-25	26+	11-15	21-25	26+
19.8%	21.5%	27.0%	9.6%	7.0%	6.9%	0.5%	0.9%	1.7%	0.7%	1.5%	3.5%

Notes: The table reports the results in Tables 6 and 7 for the case where we calibrate the U.S. economy to moments for firms (instead of plants). See Section OA-2.1 in the Online Appendix for details.

6 Conclusion

Many firms in poor countries start small, stay small, but nevertheless survive. This is very different in rich countries, where firms either exit or expand. In this paper we build a micro-founded model of firm growth to study why this is the case. The main focus of our analysis is whether cross-country differences in the efficiency of managerial delegation, as emphasized by a recent empirical literature [see e.g., Bloom and Van Reenen (2007, 2010)], can quantitatively account for the observed differences in firm dynamics. To this end, we construct a general equilibrium growth model, that allows us to connect managerial delegation, the distribution of firm size, and the degree of creative destruction, i.e., the speed with which firms lose market share and - eventually - exit. Our theory has two main ingredients. First of all, our model contains an explicit rationale for delegation: if the entrepreneur's own time is a fixed factor, firms need to delegate decision power to be able to grow large. Secondly, we allow firms to be heterogeneous in their growth potential whereby stagnant, subsistence firms survive if transformative entrepreneurs do not expand enough to replace them. Frictions in the delegation environment reduce such incentives to grow and thereby limit the degree of selection by allowing stagnant producers to survive.

aggregate in India.

[42] The main difference between plants and firms at the horizon of age 21-25 is the life-cycle, the aggregate employment share, and the relative exit rate. The life-cycle is slightly steeper, the employment share is lower (because very old firms are much bigger than very old plants), and the relative exit rate of young firms is higher than that of older plants, because old firms exit less frequently than older plants. Moreover, the aggregate entry rate is slightly lower at the firm level. In Section OA-2.1 in the Online Appendix, we provide more details on plant-firm comparison for the U.S.

We calibrate the model to data on firm growth, firm entry and exit, and managerial employment patterns independently for the U.S. and India and draw three main lessons. First of all, our model implies that the majority of Indian entrepreneurs are subsistence entrepreneurs, which are not destined to grow. At the same time, they also do not exit as transformative firms' growth incentives are also small, which reduces the degree of creative destruction in equilibrium. The existence of small firms is therefore not a sign of frictions these firms face but rather a symptom that other, more dynamic firms do not grow sufficiently. This has an important policy implication: Policies targeted at small firms could end up supporting stagnant, subsistence producers and have negative productivity consequences.

Secondly, we find that the effective delegation environment is an important determinant of firm growth in the U.S. In particular, if U.S. producers were to face the Indian delegation environment, their growth incentives would be much lower. Quantitatively, we show that differences in the delegation efficiency can account for about 25% of the observed difference in life-cycle growth between U.S. and Indian manufacturing plants.

Finally, we show that the direct effect of increases in delegation efficiency on the life-cycle of Indian firms is more limited. The reason is that there are important complementarities between the efficiency of managerial delegation and other factors affecting firm growth. In the U.S., our estimates imply that the majority of firms have ample growth potential and can hence take advantage of an efficient environment to delegate. In India, the exact opposite is the case. For improvements in the efficiency of delegation to have sizable long-run effects in India, other complementary aspects that affect firm expansion, such as financial frictions or distortionary regulations, also need to be addressed. Effective growth policies have to consider the fact that even if one of its tires is fixed, a car cannot run when the rest of the tires remain broken.

References

Acemoglu, D., U. Akcigit, N. Bloom, and W. Kerr: 2013, 'Innovation, Reallocation and Growth'. NBER Working Paper 18993.

Aghion, P., U. Akcigit, and P. Howitt: 2014, 'What Do We Learn From Schumpeterian Growth Theory?'. In: P. Aghion and S. N. Durlauf (eds.): *Handbook of Economic Growth, Volume 2*. pp. 515–563.

Aghion, P. and P. Howitt: 1992, 'A Model of Growth through Creative Destruction'. *Econometrica* **60**(2), 323–351.

Akcigit, U. and W. Kerr: 2017, 'Growth through Heterogeneous Innovations'. *Journal of Political Economy*. forthcoming.

Banerjee, A., E. Breza, E. Duflo, and C. Kinnan: 2015, 'Do Credit Constraints Limit Entrepreneurship? Heterogeneity in the Returns to Microfinance'. Working Paper.

Bento, P. and D. Restuccia: 2017, 'Misallocation, Establishment Size, and Productivity'. *American Economic Journal: Macroeconomics*. forthcoming.

Bertrand, M. and A. Schoar: 2006, 'The Role of Family in Family Firms'. *Journal of Economic Perspectives* **20**(2), 73–96.

Bloom, N., B. Eifert, T. Heller, E. Jensen, and A. Mahajan: 2009, 'Contract Enforcement and Firm Organization: Evidence from the Indian Textile Industry'. Center on Democracy, Development, and The Rule of Law Working Paper 104.

Bloom, N., B. Eifert, D. McKenzie, A. Mahajan, and J. Roberts: 2013, 'Does Management Matter: Evidence from India'. *Quarterly Journal of Economics* **128**(1), 1–51.

Bloom, N., R. Sadun, and J. Van Reenen: 2012, 'The Organization of Firms Across Countries'. *Quarterly Journal of Economics* **127**(4), 1663–1705.

Bloom, N. and J. Van Reenen: 2007, 'Measuring and Explaining Management Practices Across Firms and Countries'. *Quarterly Journal of Economics* **122**(4), 1351–1408.

Bloom, N. and J. Van Reenen: 2010, 'Why Do Management Practices Differ across Firms and Countries?'. *Journal of Economic Perspectives* **24**(1), 203–224.

Buera, F., J. Kaboski, and Y. Shin: 2011, 'Finance and Development: A Tale of Two Sectors'. *American Economic Review* **101**(5), 1964–2002.

Caselli, F. and N. Gennaioli: 2013, 'Dynastic Management'. *Economic Inquiry* **51**(1), 971–996.

Cole, H. L., J. Greenwood, and J. M. Sanchez: 2016, 'Why Doesn't Technology Flow from Rich to Poor Countries?'. *Econometrica* **84**(4), 1477–1521.

Collard-Wexler, A., J. Asker, and J. De Loecker: 2011, 'Productivity Volatility and the Misallocation of Resources in Developing Economies'. *NBER Working Paper* **17175**.

De Mel, S., D. McKenzie, and C. Woodruff: 2008, 'Returns to Capital in Microenterprises: Evidence from a Field Experiment'. *Quarterly Journal of Economics* pp. 1329–1372.

Decker, R., J. Haltiwanger, R. Jarmin, and J. Miranda: 2014, 'The Role of Entrepreneurship in US Job Creation and Economic Dynamism'. *Journal of Economic Perspectives* pp. 3–24.

Foster, L., J. Haltiwanger, and C. Syverson: 2016, 'The Slow Growth of New Plants: Learning about Demand?'. *Economica* **83**(329), 91–129.

Fukuyama, F.: 1996, *Trust: The Social Virtues and the Creation of Prosperity*, Vol. 457. Free Press New York.

Gabaix, X., J.-M. Lasry, P.-L. Lions, and B. Moll: 2016, 'The Dynamics of Inequality'. *Econometrica*. forthcoming.

Garcia-Macia, D., C.-T. Hsieh, and P. Klenow: 2015, 'How Destructive is Innovation?'. Stanford University mimeo.

Garicano, L. and E. Rossi-Hansberg: 2015, 'Knowledge-based Hierarchies: Using Organizations to Understand the Economy'. *Annual Review of Economics* **7**, 1–30.

Gennaioli, N., R. L. Porta, F. Lopez-De-Silanes, and A. Shleifer: 2013, 'Human Capital and Regional Development'. *Quarterly Journal of Economics* **128**(1), 105–164.

Gopinath, G., S. Kalemli-Ozcan, L. Karabarbounis, and C. Villegas-Sanchez: 2017, 'Capital Allocation and Productivity in South Europe'. *Quarterly Journal of Economics*. Forthcoming.

Gourio, F. and L. Rudanko: 2014, 'Customer Capital'. *Review of Economic Studies* **81**(3), 1102–1136.

Grobvosek, J.: 2015, 'Managerial Delegation, Law Enforcement, and Aggregate Productivity'. Working Paper.

Guner, N., A. Parkhomenko, and G. Ventura: 2015, 'Managers and Productivity Differences'. Working Paper.

Guner, N., G. Ventura, and Y. Xu: 2008, 'Macroeconomic Implications of Size-dependent Policies'. *Review of Economic Dynamics* **11**(4), 721–744.

Haltiwanger, J., R. Jarmin, and J. Miranda: 2013, 'Who Creates Jobs? Small Versus Large Versus Young'. *Review of Economics and Statistics* **128**(2), 347–361.

Hendricks, L. and T. Schoellman: 2016, 'Human Capital and Development Accounting: New Evidence from Wage Gains at Migration'. Working Paper.

Hopenhayn, H.: 2012, 'On the Measure of Distortions'. *Working Paper*.

Hsieh, C.-T., E. Hurst, P. Klenow, and C. Jones: 2013, 'The Allocation of Talent and U.S. Economic Growth'.

Hsieh, C.-T. and P. Klenow: 2009, 'Misallocation and Manufacturing TFP in China and India'. *Quarterly Journal of Economics* **124**(2), 771–807.

Hsieh, C.-T. and P. J. Klenow: 2014, 'The Life Cycle of Plants in India and Mexico'. *Quarterly Journal of Economics* **129**(3), 1035–1084.

Hsieh, C.-T. and B. A. Olken: 2014, 'The Missing "Missing Middle"'. *Journal of Economic Perspectives* **28**(3), 89–108.

Hurst, E. and B. Pugsley: 2012, 'What Do Small Businesses Do'. *Brookings Papers on Economic Activity*.

Jones, C.: 2013, 'Misallocation, Economic Growth and Input-Output Economics'. In: D. Acemoglu, M. Arrelano, and E. Dekel (eds.): *Advances in Econometrics: 10th World Congress*, Vol. 2. Cambridge University Press.

Klette, T. J. and S. Kortum: 2004, 'Innovating Firms and Aggregate Innovation'. *Journal of Political Economy* **112**(5), 986–1018.

La Porta, R., F. Lopez-de Silanes, A. Shleifer, and R. W. Vishny: 1997, 'Trust in Large Organizations'. *American Economic Review* **87**(2), 333–38.

La Porta, R. and A. Shleifer: 2008, 'The Unofficial Economy and Economic Development'. *Brookings Papers on Economic Activity* pp. 123–135.

La Porta, R. and A. Shleifer: 2014, 'Informality and Development'. *Journal of Economic Perspectives* pp. 109–126.

Laeven, L. and C. Woodruff: 2007, 'The Quality of the Legal System, Firm Ownership, and Firm Size'. *Review of Economics and Statistics* **89**(4), 601–614.

Lentz, R. and D. T. Mortensen: 2005, 'Productivity Growth and Worker Reallocation'. *International Economic Review* **46**(3), 731–751.

Lentz, R. and D. T. Mortensen: 2008, 'An Empirical Model of Growth through Product Innovation'. *Econometrica* **76**(6), 1317–1373.

Lentz, R. and D. T. Mortensen: 2016, 'Optimal Growth Through Product Innovation'. *Review of Economic Dynamics* **19**, 4–19.

Lucas, R. E.: 1978, 'On the Size Distribution of Business Firms'. *Bell Journal of Economics* **9**(2), 508–523.

Luttmer, E. G.: 2011, 'On the Mechanics of Firm Growth'. *Review of Economic Studies* **78**(3), 1042–1068.

Midrigan, V. and D. Y. Xu: 2014, 'Finance and Misallocation: Evidence From Plant-Level Data'. *American Economic Review* **104**(2), 422–458.

Moll, B.: 2014, 'Productivity Losses from Financial Frictions: Can Self-Financing Undo Capital Misallocation?'. *American Economic Review* **104**(10), 3186–3221.

Moscarini, G. and F. Postel-Vinay: 2012, 'The Contribution of Large and Small Employers to Job Creation in Times of High and Low Unemployment'. *American Economic Review* **102**(6), 2509–2539å.

Penrose, E. T.: 1959, *Theory of the Growth of Firms*. New York: J. Wiley & Sons.

Perla, J.: 2016, 'Product Awareness, Industry Life-Cycles, and Aggregate Profits'. Working Paper.

Peters, M.: 2016, 'Heterogeneous Mark-Ups, Growth and Endogenous Misallocation'. Working Paper.

Powell, M.: 2012, 'Productivity and Credibility in Industry Equilibrium'. Technical report, Working Paper.

Restuccia, D. and R. Rogerson: 2008, 'Policy Distortions and Aggregate Productivity with Heterogenous Establishments'. *Review of Economic Dynamics* **11**(4), 707–720.

Roys, N. and A. Seshadri: 2014, 'Economic Development and Organization of Production'. Working Paper.

Schoar, A.: 2010, 'The Divide between Subsistence and Transformational Entrepreneurship'. In: *Innovation Policy and the Economy, Volume 10*. University of Chicago Press, pp. 57–81.

Stokey, N., R. Lucas, and E. Prescott: 1989, *Recursive Methods in Economic Dynamics*. Harvard University Press, Cambridge, MA.

Ulyssea, G.: 2016, 'Firms, Informality and Development: Theory and Evidence from Brazil'. Working Paper.

Appendices

A Theoretical Appendix

A.1 Proof of Lemma 1

In Online Appendix OA-1.1 we show that $Y = Q\mathcal{M}L_P$, where $\mathcal{M}$ captures the distribution of mark-ups and L_P denotes the number of production workers. Since and $\mathcal{M}$ and L_P are constant in stationary equilibrium, the growth rate of aggregate output Y is equal to the growth rate of the aggregate productivity index Q. We can express $\ln Q_t$ after an instant Δt as

$$\begin{aligned} \ln Q_{t+\Delta t} &= \int_0^1 \left[\tau\Delta t \ln\left(\gamma q_{jt}\right) + (1-\tau\Delta t)\ln q_{jt}\right] dj \\ &= \tau\Delta t \ln(\gamma) + \ln Q_t \end{aligned}$$

where second and higher order terms in Δt are omitted. By subtracting $\ln Q_t$ from both sides, dividing by Δt, and taking the limit as $\Delta t \to 0$, we get

$$g = \frac{\dot{Q}_t}{Q_t} = \lim_{\Delta t\to 0} \frac{\ln Q_{t+\Delta t} - \ln Q_t}{\Delta t} = \tau \ln(\gamma).$$

A.2 Proof of Proposition 1: The Stationary Distribution of Firm-Size

We will now construct the stationary distribution for firm size given the equilibrium innovation schedule for high-type firms, $\{x_n\}_{n=1}^{\infty}$ and the equilibrium entry flow rate z. The stationary distribution is described by the following flow equations

$$\begin{aligned} F^L\tau_L &= z\times(1-\alpha) && (32)\\ F^H\nu_1^H\tau_H &= z\times\alpha && (33)\\ \nu_n^H n\left(\tau_H + x_n\right) &= \nu_{n-1}^H (n-1)\, x_{n-1} + \nu_{n+1}^H \tau_H (n+1) && (34) \end{aligned}$$

and the requirement that ν_n^H be a proper distribution, $\sum_{n=1}^{\infty}\nu_n^H = 1$. We need to find F^H, F^L, and $\left[\nu_n^H\right]_{n=1}^{\infty}$. Let ν_1^H and τ be given. From (25), (32) and $\tau_L = \beta\tau_H$, we get

$$\tau_H = \tau - z(1-\alpha)\left(\frac{\beta-1}{\beta}\right) \quad \text{and} \quad \tau_L = \beta\tau - z(1-\alpha)(\beta-1). \qquad (35)$$

Then, by using (32) - (34), we can calculate F^L, F^H, and $[\nu_n]_{n=2}^{\infty}$. Then we can use (24) and $\sum_{n=1}^{\infty}\nu_n^H = 1$ to find τ and ν_1^H. We now solve explicitly for these objects.

Lemma 2 *The distribution of high types takes the following form*

$$\nu_n^H n = \frac{\prod_{j=1}^n x_j}{\tau_H^n} \frac{\tau_H}{x_n} \nu_1^H. \tag{36}$$

Proof. Substituting (36) in (32) - (34) shows that if ν_n^H satisfies (36), it satisfies all the flow equations in (32) - (34). ■

This implies that $1 = \sum_{n=1}^{\infty} \nu_n^H = \nu_1^H \sum_{n=1}^{\infty} \frac{1}{n} \frac{\tau_H}{x_n} \prod_{j=1}^n \left(\frac{x_j}{\tau_H} \right)$, so that (36) reads

$$\nu_n^H = \frac{1}{n} \frac{\prod_{j=1}^n x_j}{\tau_H^n} \frac{\tau_H}{x_n} \frac{1}{\sum_{s=1}^{\infty} \frac{1}{s} \frac{\tau_H}{x_s} \prod_{j=1}^s \left(\frac{x_j}{\tau_H} \right)}. \tag{37}$$

Then, from (32) and (33), we have

$$F^H = \frac{\alpha z}{\tau_H} \times \left[\sum_{n=1}^{\infty} \frac{1}{n} \frac{\tau_H}{x_n} \prod_{j=1}^{n} \left(\frac{x_j}{\tau_H} \right) \right] \quad \text{and} \quad F^L = \frac{(1-\alpha) z}{\tau_L}.$$

Hence, we only need to determine τ, which we get from (24) as

$$\tau = \sum_{n=1}^{\infty} n x_n \nu_n^H F^H + z = \left[\sum_{n=1}^{\infty} \alpha \left(\prod_{j=1}^{n} \left(\frac{x_j}{\tau_H} \right) \right) + 1 \right] z. \tag{38}$$

Together with (35), one can show that (38) has a unique solution for τ.

B Empirical Appendix

B.1 Data

In this section we provide more information about our data sources.

Plant- and Firm-level Information for the U.S. We use data from the Business Dynamics Statistics (BDS). BDS is a product of the U.S. Census Bureau. The BDS data are compiled from the Longitudinal Business Database (LBD). The LBD is a longitudinal database of business plants and firms covering the years between 1976 and 2012. We focus on the manufacturing sector in 2012. The data are publicly available at http://www.census.gov/ces/dataproducts/bds/.

For our analysis, we utilize the following four moments from the U.S. data: (i) the cross-sectional relationship between age and size, which we refer to as the life-cycle, (ii) the aggregate employment share by age, (iii) the exit rate as a function of age *conditional on size*, and (iv) the rate of entry. For our main analysis we focus on plants. The BDS reports both aggregate employment and the number of plants by age. This allows us to calculate the first two moments. The BDS also directly reports both entry and exit rates for each size-age bin. The entry rate at the plant level is calculated as the number of new plants at time t relative to the average number of plants in t and $t-1$. Similarly, the exit rate at the plant level is calculated as the number of exiting plants in t relative to the average number of plants in t and $t-1$. The corresponding information is also reported at the firm level. In particular, the BDS reports the number of exiting firms for different size-age bin. Note that all plants owned by the firm must exit for the firm to be considered an exiting firm. As for firm entry, we treat firms of age 0 as an entering firm. Because a firm's age is derived from the age of its plants, this implies that we treat firms as entering firms only if all their plants are new. In Section OA-2.1 in the Online Appendix we provide detailed descriptive statistics about the dynamic process at both the firm- and plant-level.

Plant-Level Information for India As explained in the main body of the text, we construct a representative sample of the Indian manufacturing sector by combining data from the Annual Survey of Industries (ASI) and the National Sample Survey (NSS), which - every five years - has a special module to measure unorganized manufacturing plants. We use cross-sectional data from 2010. In contrast to the U.S., both the ASI and NSS are based on plants and we cannot link plants to firms. With the majority of employment being accounted for by very small producers, multi-plant firms are unlikely to be important for the aggregate in India. Firms in the NSS account for 99.2% of all plants and for 76% of manufacturing employment. In Section OA-2.2 in the Online Appendix we provide more detailed descriptive statistics and additional results concerning the process of firm dynamics of ASI and NSS plants.

Data on Managerial Compensation and Profits for the U.S. We identify σ from the share of managerial compensation in aggregate profits *before* managerial payments [see equation (39)]. To estimate this moment, we use two data sources. From NIPA we can retrieve a measure of aggregate profits in the manufacturing industry. Specifically, we start with aggregate corporate profits, which are directly measured in NIPA. The BEA's featured measure of corporate profits -profits from current production - provides a comprehensive and consistent economic measure of the income earned by all U.S. corporations. As such, it is unaffected by changes in tax laws, and it is adjusted for non- and misreported income. We then add to this measure non-farm proprietors' income in the manufacturing sector, which provides a comprehensive and consistent economic measure of the income earned by all U.S. unincorporated non-farm businesses.

To measure managerial wages, we augment the information in NIPA from information in the census. While NIPA reports compensation for workers, managerial payments are not directly recorded in NIPA. To calculate the managerial wage bill, we therefore use the U.S. census data. In the census we have micro data on labor compensation and occupations at the micro level. Hence, we calculate the *share* of managerial payments in the total wage bill and apply that share to the aggregate compensation data in NIPA. According to the census, managerial compensation amounts to roughly 20% of total wages. Recall that the managerial employment share in the U.S. is about 12% so that managerial wages are relatively high. We then calculate the share of managerial compensation (CSM) in aggregate profits net of managerial wages as

$$CSM = \frac{\text{Managerial Compensation}}{\text{Corporate Profits + Nonfarm Proprietor's Income + Managerial Compensation}},$$

where "Managerial Compensation" is simply 20% of the total labor compensation in NIPA. We also calculate a second measure of CSM, where we do not include “Nonfarm Proprietor’s Income." We calculate CSM before the Great Recession, because we were concerned about corporate profits being very low during the financial crisis. CSM is quite volatile. It ranges from 65% in 2001 to 33% in 2006. For our calibration we focus on the average across the years 2000 - 2007, which is 51%. If we do not include "Nonfarm Proprietor’s Income", the numbers are very similar and only slightly larger, ranging from 69% in 2001 to 35% in 2006. Hence, it is not essential for us to take "Nonfarm Proprietor’s Income" into account.

Data on Managerial Employment and Earning To measure managerial employment and earnings in the U.S. and India, we employ national Census data from the IPUMS project. We focus on the most recent year, which is 2010 for the U.S. and 2004 for India. For each country we get a sample from the census, which has detailed information about personnel characteristics. In particular we observe each respondent’s education, occupation, employment status, sex, and industry of employment. We focus on male workers in the manufacturing industry working in private-sector jobs.

The list of occupations according to ISCO is contained in Table 15. To qualify as a manager in the sense of our theory, two characteristics have to be satisfied. First, the respective individual has to work as a “Legislator, senior official, and manager.” In order to focus on managers, which are agents of a firm owner, i.e., outside managers, we *also* require workers to be wage workers and not working on their own account or to be unpaid family members. This information is also contained in the IPUMS census data in the variable “worker type." As we showed in Table 2 above, it is important to take these differences into account as poor countries have a higher share of people working on their own account (or as a family member) *conditional* on being classified as a manager according to ISCO.

TABLE 15: LIST OF OCCUPATIONS ACCORDING TO ISCO

Legislators, senior officials, and managers	Plant and machine operators and assemblers
Professionals	Elementary occupations
Technicians and associate professionals	Armed forces
Clerks	Other occupations, unspecified or n.e.c.
Service workers and shop and market sales	Response suppressed
Skilled agricultural and fishery workers	Unknown
Crafts and related trades workers	NIU (not in universe)

Notes: Table 15 contains the occupational categories available in the IPUMS data. A necessary condition for someone to be classified as an outside manager is to be assigned the occupational title "Legislators, senior officials, and managers." See the main body of the text for the additional requirements.

B.2 Identification of the Model

This section contains additional details about the identification in our model. Consider first Table 16, which contains a sensitivity matrix for our calibration moments. More specifically, we take the US calibration and then independently vary each parameter by 1% starting from its calibrated value. We report the implied percentage change in the different moments. As highlighted above: the share of high-type firms α affects the relative exit rate (M2), the efficiency of expansion θ affects the life-cycle (M4) and the delegation efficiency (together with managerial skill supplies) $\xi \times \mu$ determine the equilibrium managerial share. Also note that the equilibrium step size γ only affects the equilibrium growth rate and leaves all other moments unchanged.

TABLE 16: MOMENT SENSITIVITY

		α	β	γ	θ	$\xi \times \mu$	ϑ	θ_E	T	σ
M1.	Empl. share of 21-25-year-old firms	0.62	-0.01	0.00	-0.11	0.11	-0.17	0.66	0.20	-0.36
M2.	Rel. exit rate of small 21-25-year-old firms	-0.85	-0.16	0.00	-0.35	-0.26	0.28	-0.10	-0.05	0.66
M3.	Aggregate growth rate	0.07	0.00	7.40	0.88	0.61	-0.68	0.25	0.15	-1.58
M4.	Mean empl. of 21-25-year-old firms	-0.38	-0.02	0.00	0.61	0.26	-0.21	-0.32	-0.01	-0.63
M5.	Share of managers in the workforce	0.02	0.00	0.00	-0.02	1.41	0.85	0.02	0.03	-0.53
M6.	Variance of log manager wage	0.00	0.00	0.00	0.00	0.00	-2.00	0.00	0.00	0.00
M7.	Entry rate	-0.15	0.00	0.00	0.27	0.57	-0.65	0.85	0.17	-1.48
M8.	Share of entrepreneurial profit	0.17	-0.01	0.00	-0.20	0.52	-0.44	0.20	0.25	-1.92
M9.	Share of manager compensation	-0.09	0.01	0.00	0.11	0.20	-0.17	-0.11	-0.14	0.92
M10.	Employment share of no-manager firms					*See Table Notes*				
M11.	Rel. manager share of Indian migrants					*See Table Notes*				

Notes: The table presents the elasticity for each moment used the internal calibration with respect to the parameters of the model. In particular, we report percentage change in the moment for a 1% change in the parameter from its benchmark value in the U.S. calibration, while keeping the rest of the parameters at their benchmark values. We report the average elasticities based on +1% and -1% changes. Our calibration for the U.S. implies that the employment share of no-manager firms (M10) is zero, i.e., all the firms hire managers. Due to the discrete nature of the extensive margin of managerial hiring, M10 does not move as a response to a small change in the parameters. The relative manager share of Indian migrants (M11) is used identify the relative managerial skill supply of workers in India relative to the U.S., $\frac{\mu_{M,IND}}{\mu_{M,US}}$.

We will now discuss the identification of our model in more detail. In total, there are 10 parameters to identify[43]:

$$(T, \sigma, \xi, \alpha, \theta, \theta_E, \beta, \gamma, \mu_M, \vartheta).$$

In Section A.2, we showed that there exists a unique stationary distribution of firm size given the optimal innovation and entry rates $\{x_n\}_{n=1}^{\infty}$ and z. More specifically, $\{x_n\}_{n=1}^{\infty}$ and z determine the aggregate innovation rate τ and these three objects together uniquely pin down the joint distribution of age and size, i.e., the entire process of firm-dynamics. The four parameters that affect this process directly are $(\theta, \theta_E, \beta, \alpha)$. We therefore use the following four firm-level moments to calibrate these parameters: (i) the life cycle, i.e., the relative size of firms of age 21-25 to firms of age 1-5, (ii) the share of aggregate employment accounted for by firms of age 21-25, (iii) the relative exit rate of 1-5 year old firms relative firms of age 21-25 conditional on size, and (iv) the entry rate. Intuitively, the slope of the life-cycle is informative about θ, which determines the level of incumbent's innovation effort. As β effectively controls the size of old cohorts (by determining the speed with which high-type firms exit), it is related to the aggregate importance of old cohorts in the economy, i.e., the relative employment share of old firms. The exit hazard conditional on size is informative about the degree of selection. If there was no type heterogeneity, the exit rate would only be a function of size. To the extent that older firms are positively selected, they are less likely to exit conditional on size. The ex-ante heterogeneity α determines how strong this effect can be. Finally, the entry rate is informative about θ_E. Moreover, after pinning down the firm size distribution, we can calibrate the step-size γ to fit the aggregate growth rate as $g = \ln(\gamma)\tau$.

We then use several moments related to managerial employment patterns - namely the compensation of managers relative to corporate profits, the entrepreneurial share in total compensation, the dispersion of managerial wages, and managerial employment shares - to identify σ, T, ϑ, ξ and μ_M. Consider first σ, the elasticity of profits with respect to managerial services.[44] In the model, the total compensation for managerial personnel relative to aggregate profits (before managerial payments) is given by

$$\frac{w_M H^M}{\Pi + w_M H^M} = \frac{\sum_{n=1}^{\infty} w_M \times n \times m(n) \times \varphi_n}{\sum_{n=1}^{\infty} e(n)^{\sigma} Y \times n \times \varphi_n},$$

where $\varphi_n = F^H \nu_n^H$ and $\varphi_1 = F^H \nu_1^H + F^L$ is the endogenous firm size distribution. By using $m(n) = T\xi^{-1} \times \max\{0, (n^*)^{-1} - (n)^{-1}\}$, $\omega_M \equiv \frac{w_M}{Y} = \sigma\xi\left(\frac{n^*}{T}\right)^{1-\sigma}$ and $e(n) = T\max\{n^{-1}, (n^*)^{-1}\}$, we get that

$$\frac{w_M H^M}{\Pi + w_M H^M} = \sigma \frac{\sum_{n=1}^{\infty} (n^*)^{1-\sigma} \left(\max\left\{0, \frac{1}{n^*} - \frac{1}{n}\right\}\right) \times n \times \varphi_n}{\sum_{n=1}^{\infty} \left(\max\left\{\frac{1}{n}, \frac{1}{n^*}\right\}\right)^{\sigma} \times n \times \varphi_n}. \tag{39}$$

[43]Recall that we calibrate ζ and ρ outside of the model.

[44]Although the specific ordering of parameters in the identification discussion is not essential, it facilitates the argument.

Hence, conditional on n^* and the firm size distribution, (39) only depends on σ.

To determine T, we target the share of income accruing to entrepreneurs after paying for their factors of production. As entrepreneurs are the residual claimants on firm profits, this moment is simply given by

$$\begin{aligned}\frac{\Pi}{Y} &= \sum_{n=1}^{\infty}\left[e(n)^{\sigma}-\omega_M m(n)\right]\times n\times\varphi_n\\ &= T^{\sigma}\sum_{n=1}^{\infty}\left[\left(\max\left\{n^{-1},(n^*)^{-1}\right\}\right)^{\sigma}-\sigma n^*\max\left\{0,\frac{1}{n^*}-\frac{1}{n}\right\}\right]\times n\times\varphi_n,\end{aligned}$$

which is directly informative about T for given n^*, φ_n, and σ.

The shape parameter of skill distribution ϑ can be identified directly from the dispersion of managerial earnings. To see this, note that the earnings of a manager with relative skill h is $w_M h$. The distribution of managerial earning is therefore given by

$$P\left[w_M h > x | h \geq \frac{w_P}{w_M}\right] = \left(\frac{w_P/w_M}{x/w_M}\right)^{\vartheta} = \left(\frac{w_P}{x}\right)^{\vartheta},$$

which is pareto with shape ϑ and location w_P. Defining the relative managerial earnings $y \equiv \ln\left(\frac{w_M h}{w_P}\right)$, we get $P\left(y \leq y_0\right) = 1 - e^{-\vartheta y_0}$, so that

$$var\left(y\right) = var\left(ln\left(\frac{w_M h}{w_P}\right)\right) = var\left(ln\left(w_M h\right)\right) = \vartheta^{-2}.$$

Hence, we can calibrate ϑ directly to the variance of log managerial earnings.

Finally, we identify ξ and μ_M by using the share of managers in the whole economy *and* among Indian immigrants to the U.S. economy. Recall that the equilibrium managerial employment share is given by

$$\lambda = P\left[h_M w_M \geq w_P\right] = \left(\frac{\frac{\vartheta-1}{\vartheta}\mu_M}{w_P/w_M}\right)^{\vartheta} = \left(\frac{\vartheta-1}{\vartheta}\mu_M\frac{\sigma\xi}{\omega_P}\left(\frac{n^*}{T}\right)^{1-\sigma}\right)^{\vartheta}.$$

Using the expression for total managerial demand, the equilibrium condition for the managerial labor market can be written as

$$\mu_M\xi = \left(\lambda\right)^{-\frac{\vartheta-1}{\vartheta}}\times\sum_{n\geq n^*}^{\infty}T\left(\frac{1}{n^*}-\frac{1}{n}\right)\times n\times\varphi_n. \tag{40}$$

Hence, given n^*, T, ϑ, and φ_n, we can directly determine $\mu_M\times\xi$ from the data on the share of managers in the whole population (i.e., λ). To separate the effect of managerial human capital (μ_M) from delegation efficiency (ξ), we use data on managerial employment pattern of Indian immigrants. Because our approach uses additional data and because all allocations in the model only depend on $\mu_M\times\xi$, we discuss the details of our strategy in Section B.3. Once we identify

μ_M, we get ξ from (40).

B.3 Identifying Managerial Skill Supplies μ_M

In this section, we derive equation (31) in the main text to clarify the identification of μ_M. To decompose differences in the managerial environment in India and the U.S. into supply and demand factors, we start out with 4 parameters: $(\mu_{M,US}, \xi_{US}, \mu_{M,IND}, \xi_{IND})$. Without loss of generality we can normalize $\mu_{M,US} = 1$. Since $\mu_{M,c} \times \xi_c$ is identified from the equilibrium managerial employment shares [see (40)], we require one additional equation to determine the relative managerial human capital in India, $\mu_{M,IND}$. To do so, we use data on employment patterns of immigrants from India to the U.S.

Let λ_c be the managerial share of the native population in country c. Let λ^M_{IND} be the managerial employment share in the population of Indian migrants in India (i.e., pre-migration). Let λ^M_{US} be the managerial employment share in the population of Indian migrants in the U.S. (i.e., post-migration). Suppose that the distribution of managerial ability of Indians who migrate to the U.S. is distributed Pareto with shape ϑ and mean $\hat{\mu}_{M,IND}$. If $\hat{\mu}_{M,IND} = \mu_{M,IND}$, migration is orthogonal to managerial skills. If $\hat{\mu}_{M,IND} > \mu_{M,IND}$, migrants have, on average, a comparative advantage in managerial work. Given these assumptions it follows that

$$\lambda_c = \tilde{\vartheta}\left(\omega^c_M\right)^{\vartheta}\left(\mu_{M,c}\right)^{\vartheta} \quad \text{and} \quad \lambda^M_c = \tilde{\vartheta}\left(\omega^c_M\right)^{\vartheta}\left(\hat{\mu}_{M,c}\right)^{\vartheta}$$

where $\tilde{\vartheta} = \left(\frac{\vartheta-1}{\vartheta}\right)^{\vartheta}$ and ω^c_M is the relative managerial wage $\frac{w_M}{w_P}$ in country c. Hence,

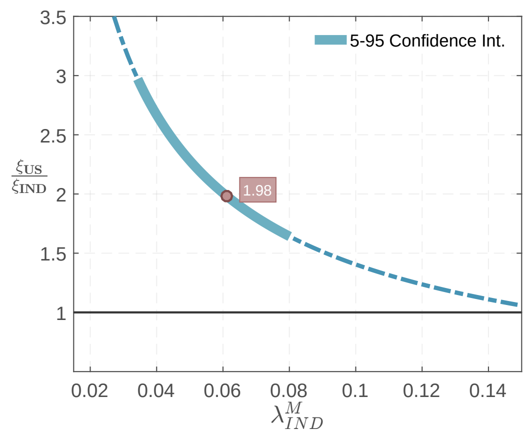
$$\frac{\mu_{M,IND}}{\mu_{M,US}} = \left(\frac{\lambda_{IND}}{\lambda^M_{IND}} \times \frac{\lambda^M_{US}}{\lambda_{US}}\right)^{1/\vartheta}. \tag{41}$$

Note that we already calibrated ϑ and we already used λ_{IND} and λ_{US} in our calibration. λ^M_{IND} is directly observable in the U.S. Census, because we see the employment structure among recent Indian immigrants. Finally, λ^M_{IND} can be estimated from the New Immigration Study, which explicitly asks immigrants about the occupations *prior* to migration [see Hendricks and Schoellman (2016)].

The data to quantify (41) is contained in Table 5 in the main text. Columns 1 and 3 report the managerial share in the U.S. and India, respectively. In column 2 we report the managerial share among Indian immigrants in the U.S. To ensure that this population is informative about the human capital of recent Indian migrants, we restrict the sample to migrants that arrived in the U.S. within the last 5 years. The managerial share in this population is given by 12.9%. In the last column we exploit information from the New Immigration Study to measure the share of migrants that used to work as managers in India. We find that roughly 6% of them worked as outside manager.

The sample size for estimating the managerial share of migrants in India, λ^M_{IND}, is only 403, i.e., quite small. To judge the robustness of our results, we report the implied differences in delegation quality $\frac{\xi_{US}}{\xi_{IND}}$ as a function of the point estimate of λ_{IND}^{M}. We treat the other empirical objects in (41), as fixed as these are precisely estimated. Furthermore, we treat $\xi_c^{Eff} \equiv \mu_{M,c}\xi_c$ as parametric, as it can be calibrated without using the information on λ_{IND}^{M}. We construct the confidence intervals for $\frac{\xi_{US}}{\xi_{IND}}$ using a Bootstrap procedure, where we repeatedly draw samples of the same sample size from the New Immigration Study data and calculate λ_{IND}^{M}. The results of this exercise are contained in Figure 9. We find that the relative delegation efficiency of the U.S. is between 1.6 and 2.9 of the one in India with 90% probability. We also want to stress that this uncertainty *only* affects the decomposition of the implied counterfactual into the human capital and the delegation efficiency component, as all allocation only depend on $\mu_{M,c}\xi_c$, which is calibrated directly in the model.

FIGURE 9: CALIBRATING $\frac{\xi_{US}}{\xi_{IND}}$



Notes: The figure depicts the resulting $\frac{\xi_{US}}{\xi_{IND}} = \frac{\xi_{US}^{Eff}}{\xi_{IND}^{Eff}}\frac{\mu_{M,IND}}{\mu_{M,US}}$ as a function of λ_{IND}^{M} [see equation (41)]. Our point estimate for the immigrants' managerial share in India (6.1%) yields a relative delegation quality of 1.84. The 5-to-95 confidence interval around that value ranges from about 1.6 to 2.9.

B.4 Reduced-Form Evidence based on Variation across Indian Plants

In Section 3.2, we reported some basic patterns on managerial hiring and firm size from the Indian micro data and discussed how they relate to our theory. This section describes this analysis in more detail.

Our empirical investigation mainly focuses on the implications of two parameters of our model: (i) the entrepreneur's time endowment T and (ii) the delegation efficiency ξ. In the theory, the time endowment of entrepreneurs T has the interpretation that it can neither be sold on the market, nor is there any need to monitor. The NSS data for 1995 contains information on the size of the family of the plant's owner. As long as family members require less monitoring than outside managers, we can think of family size as inducing variation in the time endowment T. As for the delegation efficiency ξ, we will rely on the variation in trust across 22 Indian states. The Indian micro data contain information about the state in which the respective plant is located. Additionally, we extract information on the general level of trust between people at the state level from the World Value Surveys. The World Values Survey is a collection of surveys based on representative samples of individuals and provides an index of trust in different regions of India. The primary index we use is derived from the answers to the question "Generally speaking, would you say that most people can be trusted, or that you can not be too careful in dealing with people?". Following Bloom et al. (2012) and La Porta et al. (1997), the regional trust index is constructed as the percentage of people providing the answer "Most people can be trusted" within the state where the firm is located. This is the most common measure of trust used in the literature. While this variable is not directly aimed at eliciting the (perceived) quality of the prevailing legal environment, it fits well into our theoretical framework as long as trust reduces the required time the owner needs to spend to incentivize outside managers. See also Bloom et al. (2012), who also use this variable to proxy the efficiency with which decisions can be delegated.

In Table 17, we look at some of the implications of our theory based on the above-mentioned proxies. We first focus on the extensive margin of managerial hiring. In the model, a firm hires an outside manager only when its size n is above a certain (endogenous) threshold which we denote as n^*

$$n^* \equiv T \times \left(\frac{\omega_M}{\sigma\xi}\right)^{\frac{1}{1-\sigma}}.$$

For the purpose of the empirical analysis, in addition to firm size n, suppose that firms also differ in (i) owner's time endowment T and (ii) delegation efficiency ξ. Then, the extensive margin of managerial hiring decision for firm f can be summarized as

$$\begin{aligned}
\mathbb{1}\left[Manager_f > 0\right] &= \mathbb{1}\left[n_f \geq n_f^*\right] \\
&= \mathbb{1}\left[n_f \geq T_f \times \left(\frac{\omega_M}{\sigma\xi_f}\right)^{\frac{1}{1-\sigma}}\right] \\
&= \mathbb{1}\left[\log n_f - \log T_f + \frac{1}{1-\sigma} \times \log \xi_f + const. \geq 0\right]
\end{aligned}$$

where subscript f indicates firm specific values and $const.$ includes all terms that are not firm specific. This relation can be converted to an *estimable* one by introducing some stochasticity. In particular, by introducing a uniformly distributed random variable, which can be considered as measurement error, to the RHS of the above equation and taking the expectation of both sides, we get

$$\mathbb{P}\left(Manager_f > 0\right) = \beta_0 + \beta_1 \log n_f - \beta_2 \log T_f + \beta_3 \log \xi_f \tag{42}$$

This equation implies that the likelihood of hiring a manager should be increasing in firm size and delegation efficiency and declining in the owner's time endowment. To test these predictions empirically, we estimate the coefficients of (42) by using the proxy variables mentioned above.[45] Column 1 of Table 17 summarizes the results. It suggests that the predictions of the model regarding the extensive margin of managerial hiring are in line with the data: large firms and firms in states with favorable trust measures are more likely to hire outside managers, while firms with larger families abstain from hiring outside managerial personnel holding firm size constant.

Table 17: Managerial Hiring, Firms Size and Growth in India

	Dependent Variable				
	Manager >0	Log empl (Manager >0)		Log empl	
Log Empl	0.039***				
	(0.003)				
Log HH Size	-0.003**	0.927***	0.812***	0.224***	0.235***
	(0.001)	(0.306)	(0.278)	(0.033)	(0.032)
Trust	0.013**	3.264**		0.094	
	(0.006)	(1.628)		(0.174)	
Log HH Size* Trust		-1.694**	-1.329*	0.036	0.028
		(0.818)	(0.758)	(0.093)	(0.090)
State FE	N	N	Y	N	Y
N	178,999	2,350	2,350	178,999	178,999
R^2	0.04	0.42	0.50	0.18	0.20

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. All regressions include 2-digit fixed effects, the age of the plant, year dummies, and a dummy variable for the plant to be in a rural area as control variables. For the regressions that do not include state-level fixed effects, log GDP per capita at the state level is included as a control variable. "Log Empl" denotes the (log of) total employment at the plant. "Log HH size" denotes the (log of) the size of the household of the plant's owner. This variable is only available for the NSS data. "Trust" is the measure of trust at the state level, which we calculate from the World Value Surveys. The dependent variables are: an indicator of managerial hiring (column 1), log employment conditional on managerial hiring (columns 2 - 3), log employment (columns 4-5).

These static determinants of managerial hiring have dynamic implications relating to firms' expansion incentives and hence firm size. In particular, conditional on hiring managers, growth incentives and hence firm size are increasing in delegation efficiency. Our theory implies that delegation efficiency ξ and the owner's time endowment T are substitutes, i.e., we should expect a tighter link between family size and firm size in low-trust regions. Columns 2 and 3 show that this is the case. First, similar to Bloom et al. (2013), we also find a tight relationship between firm size and family size. We interpret this correlation as family members substituting for the scarcity of available outside managers. Furthermore, the coefficient on the interaction term is negative, which means that the positive relationship between firm size and family size is weaker in regions

[45]Note that (42) implies a linear probability model and its parameters can be estimated using OLS. We also include additional control variables in the regression. Details are given in the notes under Table 17.

where trust is higher and hence delegation is more efficient.[46] In column 3, we replicate these results with state fixed effects to control for all time-invariant regional characteristics.

In columns 4 and 5, we redo the analysis of columns 2 and 3 for the whole sample of firms, i.e., we do not condition on delegation. Again we find a positive correlation between the size of the family and firm size. Note that the effect of trust for the entire sample of firms is much weaker. This is consistent with our theory, which implies that delegation efficiency only matters for the firms that actually delegate. For firms without outside managers (i.e., firms with $n < n^*$), growth incentives are only determined by the owner's time endowment T.

Finally, we replicated the entire analysis of Table 17, which controlled for 2-digit sector fixed effects, with 3-sector fixed effects. The results are contained in Table 18. It is seen that results are similar. The only exception are the results in columns 2 and 3, which are conditioned on managerial hiring and hence have a small sample size[47]. While all point estimates are of the same sign, they are not significantly different from zero.

Table 18: Managerial Hiring, Firms Size and Growth in India: Robustness

	Dependent Variable				
	Manager > 0	Log empl (Manager > 0)		Log empl	
Log Empl	0.040***				
	(0.003)				
Log HH Size	-0.004***	0.389	0.394*	0.207***	0.220***
	(0.001)	(0.248)	(0.231)	(0.030)	(0.030)
Trust	0.012*	0.570		-0.008	
	(0.006)	(1.300)		(0.160)	
Log HH Size* Trust		-0.443	-0.359	0.062	0.040
		(0.658)	(0.614)	(0.086)	(0.084)
State FE	N	N	Y	N	Y
N	178,999	2,350	2,350	178,999	178,999
R^2	0.05	0.58	0.63	0.28	0.30

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. All regressions include 3-digit fixed effects, the age of the plant, and a dummy variable for the plant to be in a rural area as control variables. For the regressions that do not include state level fixed effects, log GDP per capita at the state-level is included as a control variable. "Log Empl" denotes the (log of) total employment at the plant. "Log HH size" denotes the (log of) the size of the household of the plant's owner. This variable is only available for the NSS data. "Trust" is the measure of trust at the state level, which we calculate from the World Value Surveys. The dependent variables are: an indicator of managerial hiring (column 1), log employment conditional on managerial hiring (columns 2 - 3), log employment (columns 4-5).

[46] In a separate regression, not shown here, we also control for the assets of the firm as both family size and the level of regional trust could be correlated with the supply of capital to the firm. The results are very similar.

[47] Given the small sample size, finer controls for sector fixed effect leave less variation in the data for the relations we are interested in.

Online Appendix for "Lack of Selection and Limits to Delegation: Firm Dynamics in Developing Countries"

by Ufuk Akcigit, Harun Alp, Michael Peters

April 14, 2017

- Not for Publication Unless Requested -

OA-1 Online Appendix - Theory

OA-1.1 Static Equilibrium

Consider the equilibrium in the product market. At each point in time, each product line j is produced by a single firm with productivity q_{jt}. We normalize the price of aggregate output Y to one. As firms set a price equal to $p_{jf} = q_{jf}^{-1} w_t$ we get that

$$\ln(Y) \quad = \quad \int_0^1 \ln(y_j)dj = \int_0^1 \ln(p_j y_j)dj - \int_0^1 \ln(p_j)dj = \ln(Y) - \ln(w_P) + \int_0^1 \ln(q_j)dj$$

which implies $w_P = Q \equiv \exp\left[\int_0^1 \ln q_j dj\right]$. The production function [see equation (4)] also implies that

$$\ln(L^P) \quad = \quad \int_0^1 \ln(l_j)dj = \int_0^1 \ln(y_j)dj - \int_0^1 \ln(q_j)dj - \int_0^1 \ln(\mu(e_j))dj, \qquad \text{(OA-1)}$$

where L^P is the aggregate demand for production labor. Then, we get $L^P = \frac{Y}{Q\mathcal{M}} = \frac{1}{\mathcal{M}}\frac{1}{\omega_P}$ where $\omega_P = \frac{w_P}{Y}$ and $\mathcal{M}$ is defined as

$$\mathcal{M} = \left[1 - \sum_{n=1}^{\infty} (e(n))^{\sigma} \times n \times \left(\nu_n^H F^H + \nu_n^L F^L\right)\right]^{-1}$$

where function $e(.)$ is defined in (7), ν_n^i and F^i are the size distribution and the measure of i-type firms, $i \in \{H, L\}$, respectively (see Proposition 1).

OA-1.2 A Simple Microfoundation for ξ

In this section, we provide a simple example of how ξ could depend on various institutional parameters in an economy. Please note that none of the analysis in the main text depends on this particular example. This example is provided to fix ideas.

Suppose that both managers and entrepreneurs each have one unit of time at their disposal. While the latter can provide T units of effort during that time interval, managers can provide 1 unit of effort. Suppose that the provision of managerial effort is subject to contractual frictions. For simplicity, assume that the manager can decide to either provide effort or shirk, in which case he adds no usable services to the firm. The firms can translate each unit of managerial effort into η units of managerial services.

While the manager's effort choice is not contractible, the entrepreneur can monitor the manager to prevent him from shirking. If the entrepreneur spends s units of her time monitoring the manager, she will catch a shirking manager with probability s. Whenever the manager shirks and gets caught, the entrepreneur can go to court and sue the manager for the managerial wage w. In particular, the court (rightly) decides in the entrepreneur's favor with probability κ. Hence one can think of κ as parameterizing the efficiency of the legal system. Finally, the demand for shirking arises because shirking carries a private benefit bw, where $b < 1$.[48]

It is straightforward to characterize the equilibrium of this simple game. If the entrepreneur spends s units of her time monitoring the manager, the manager does not shirk if and only if

$$w \geq bw + w\left(1 - \kappa s\right),$$

where $(1 - \kappa s)$ is the probability that the manager gets paid despite having shirked. Clearly the owner will never employ a manager without inducing effort. Hence, the owner will spend $s = b/\kappa$ units of time monitoring the manager. The overall amount of managerial services in product line j is therefore given by[49]

$$e_j = \frac{T}{n} - m_j s + \eta m_j \quad = \quad \frac{T}{n} + \left(\eta - \frac{b}{\kappa}\right) \times m_j = \frac{T}{n} + \xi\left(\kappa, \eta, b\right) \times m_j. \tag{OA-2}$$

Hence, ξ measures precisely the net increase in managerial services through delegation. In particular, the delegation efficiency is increasing in the firm's efficiency to employ managers (η) and in the state of the contractual environment (κ), because monitoring and the strength of the legal system are substitutes. Note also that the whole purpose of delegation is to increase a firm's managerial resources, so that firms will never hire a manager if $\xi\left(\kappa, \eta\right) \leq 0$. Hence, whenever managers are sufficiently unproductive or the quality of legal systems is sufficiently low, firms will never want to hire outside managers because owners need to spend more of their own time to prevent the opportunistic behavior of managers than they gain in return.

[48]The necessity for the private benefit being proportional to the wage arises in order to make the contract stationary.

[49]Note that we do not require that $s < T$, i.e., we do not require the owner to perform the monitoring himself. We rather think of managerial efficiency units to be perfect substitutes within the firm, i.e., an owner can hire a manager to monitor other managers.

OA-1.3 Stationary Equilibrium of the Model

In this section, we describe the stationary equilibrium of the model in detail. To do so, we proceed in two steps.

Step 1 Fix $s \equiv (n^*, \omega_P)$ where n^* and ω_P are delegation cut-off and normalized wage rate for production workers, respectively. By using (28) and (29), we can write the rate of destruction for high types $\tau_H(s)$ as

$$\tau_H(s) = z(s) \times \left\{ \left[\alpha \sum_{h=1}^{\infty} \prod_{j=1}^{h} \left(\frac{x_j(s)}{\tau_H(s)} \right) \right] + 1 - (1-\alpha) \left(\frac{\beta - 1}{\beta} \right) \right\}, \tag{OA-3}$$

where $[x_j(s)]_{j=1}^{\infty}$ is the optimal innovation policy by high types implicitly defined in (17) and $z(s)$ is the optimal entry rate. We focus on a solution where $x_j < \tau_H$ for all τ_H. This is a sufficient condition for a stationary solution.[50] We will show below that such a solution exists for all s provided that θ_E is large enough.

Let $v_H(n)$ be normalized value function of a high-type firm.[51] It satisfies

$$\rho v_H(n) = \max_{x_n} \left\{ \tilde{\pi}(n; n^*) - \omega_p \theta^{-\frac{1}{\zeta}} n x_n^{\frac{1}{\zeta}} + x_n n \left[v_H(n+1) - v_H(n) \right] + \tau_H n \left[v_H(n-1) - v_H(n) \right] \right\}.$$

where we use the fact that $w_p = Q$ to substitute $\frac{Q}{Y}$ with ω_P.[52] By rearranging terms and explicitly imposing the restriction $x_j < \tau_H$, we can write v_H as

$$v_H(n) = n \times \max_{x_n < \tau_H} \left\{ \frac{\frac{\tilde{\pi}(n;n^*)}{n} - \omega_p \theta^{-\frac{1}{\zeta}} x_n^{\frac{1}{\zeta}} + x_n v_H(n+1) + \tau_H v_H(n-1)}{\rho + (x_n + \tau_H) n} \right\}.$$

Now consider the function $b(n) \equiv \frac{v_H(n)}{n}$, which - by using the above equation - can be written as

$$b(n) = \max_{x_n < \tau_H} \left\{ h(n, x_n) + \frac{x_n (n+1)}{\rho + (x_n + \tau_H) n} b(n+1) + \frac{\tau_H (n-1)}{\rho + (x_n + \tau_H) n} b(n-1) \right\}, \tag{OA-4}$$

where $h(n, x_n) \equiv \frac{\frac{\tilde{\pi}(n;n^*)}{n} - \omega_p \theta^{-\frac{1}{\zeta}} x_n^{\frac{1}{\zeta}}}{\rho + (x_n + \tau_H) n}$.

We will show that the right-hand side of (OA-4) satisfies Blackwell's sufficient conditions for a contraction. To see this, define the operator T by

$$(Tf)(n) \equiv \max_{x_n < \tau_H} \left\{ h(n, x_n) + \frac{x_n (n+1)}{\rho + (x_n + \tau_H) n} f(n+1) + \frac{\tau_H (n-1)}{\rho + (x_n + \tau_H) n} f(n-1) \right\}. \tag{OA-5}$$

[50] A necessary condition is that there exists $\hat{n}$ with $x_j < \tau_H$ for all $j > \hat{n}$.
[51] We drop the dependence of the value function on s for notational clarity.
[52] See Section OA-1.1 for details.

Hence, b can be defined as a fixed point of T, i.e., a function such that $(Tb)(n) = b(n)$. First, note that $h(n, x_n)$ is bounded [see (11)] so that T maps the space of continuous bounded functions into itself (Berge's Maximum Theorem). Moreover, for any continuous bounded functions f, g with $f(n) \leq g(n)$ for all $n \in Z^{++}$, we have

$$\begin{aligned}
(Tf)(n) &= \max_{x_n<\tau_H}\left\{h(n,x_n) + \frac{x_n(n+1)}{\rho+(x_n+\tau_H)n}f(n+1) + \frac{\tau_H(n-1)}{\rho+(x_n+\tau_H)n}f(n-1)\right\} \\
&\leq \max_{x_n<\tau_H}\left\{h(n,x_n) + \frac{x_n(n+1)}{\rho+(x_n+\tau_H)n}g(n+1) + \frac{\tau_H(n-1)}{\rho+(x_n+\tau_H)n}g(n-1)\right\} \\
&= (Tg)(n),
\end{aligned}$$

so that the monotonicity condition is satisfied. Lastly, for any continuous bounded function f and $a \geq 0$,

$$\begin{aligned}
(T[f+a])(n) &= \max_{x_n<\tau_H}\left\{h(n,x_n) + \frac{x_n(n+1)}{\rho+(x_n+\tau_H)n}[f(n+1)+a] + \frac{\tau_H(n-1)}{\rho+(x_n+\tau_H)n}[f(n-1)+a]\right\} \\
&\leq \max_{x_n<\tau_H}\left\{h(n,x_n) + \frac{x_n(n+1)}{\rho+(x_n+\tau_H)n}f(n+1) + \frac{\tau_H(n-1)}{\rho+(x_n+\tau_H)n}f(n-1)\right\} + \Omega a \\
&= (TF)(n) + \Omega a
\end{aligned}$$

where

$$\Omega \equiv \max_{x_n<\tau_H}\left\{\frac{(x_n+\tau_H)n}{\rho+(x_n+\tau_H)n} + \frac{x_n-\tau_H}{\rho+(x_n+\tau_H)n}\right\} < 1.$$

Hence, the operator T satisfies the discounting condition, so that T is a contraction mapping and therefore posses a unique fixed point [Stokey et al. (1989)], which is continuous in s and τ_H. Moreover, the expression inside the max operator in (OA-5) is continuous in x_n and strictly concave so that Berge's Maximum Theorem implies that the set of maximizers x_n^* is a continuous function of s and τ_H. The equilibrium entry rate z is fully determined from v_H and v_L [see (21)] and hence also a continuous function of s and τ_H.[53]

Hence, equation (OA-3) is continuous in τ_H. To see that there exists a fixed point for τ_H, note that the RHS is bounded away from zero because $z(s) > 0$ and that it is bounded from above. To see that, note that $\sum_{h=1}^{\infty}\prod_{j=1}^{h}\left(\frac{x_j(s)}{\tau_H(s)}\right)$ is bounded in a stationary equilibrium and that z is bounded [see (21)]. Hence, there exits a fixed point for τ_H. Moreover, because z is increasing in θ_E for a given s and τ_H, (OA-3) implies that for each s there is θ_E large enough such that this fixed point satisfies $\tau_H > x_n$.

Step 2 We can now represent the whole model in terms of labor market clearing conditions. Given Step 1, we can calculate the firm size distribution $\varphi_n(s) = \nu_n^H(s)F^H(s) + \nu_n^L(s)F^L(s)$ from Proposition 1. From (12), (22), and (23), the labor market clearing conditions for managers and

[53] Recall that $v_L(1) = \frac{\pi(1)}{\rho+\tau_L}$, where $\tau_L = \beta \times \tau_H$.

production workers can then be written by

$$0 = \left(\frac{\vartheta-1}{\vartheta}\mu_M\right)^{\vartheta}\left(\frac{(n^*)^{1-\sigma}\sigma\xi}{T^{1-\sigma}\omega_P}\right)^{\vartheta-1}\frac{\vartheta}{\vartheta-1} - \frac{T}{\xi}\sum_{n>n*}\left(\frac{1}{n^*}-\frac{1}{n}\right)n\varphi_n(s) \tag{OA-6}$$

$$0 = 1-\left(\frac{\vartheta-1}{\vartheta}\mu_M\right)^{\vartheta}\left(\frac{(n^*)^{1-\sigma}\sigma\xi}{T^{1-\sigma}\omega_P}\right)^{\vartheta} - \frac{1}{\omega_P}\left[1-\sum_{n=1}^{\infty}\left(\max\left\{\frac{T}{n},\frac{T}{n^*}\right\}\right)^{\sigma}n\varphi_n(s)\right] \tag{OA-7}$$

where two equations depend only on $s \equiv (n^*, \omega_P)$. Note that $\varphi_n(s)$ is continuous in z, τ_H and x_n. Therefore, from Step 1, left-hand-side of both equations are continuous in (n^*, ω_P). Solution to the system of equation given by (OA-6) and (OA-7) constitutes an equilibrium for our economy.

OA-2 Online Appendix - Empirical Analysis

OA-2.1 Firms vs. Plants in the U.S. Manufacturing Sector

In this section we compare the process of firm-dynamics across U.S. manufacturing firms and plants. Table OA-1 provides some summary statistics about the size-distribution of firms and plants in the U.S. The average manufacturing firm in the U.S. has 51 employees, while the average plant only 43. It is also the case that large firms have multiple plants (firms with more than 1000 employees have on average 13) so that large firms account for half of total employment. There is a lower concentration at the plant level in that plants with more than 1000 employees account for less than one-fifth of aggregate employment in manufacturing in the U.S.

Table OA-1: Descriptive Statistics: U.S. Micro Data

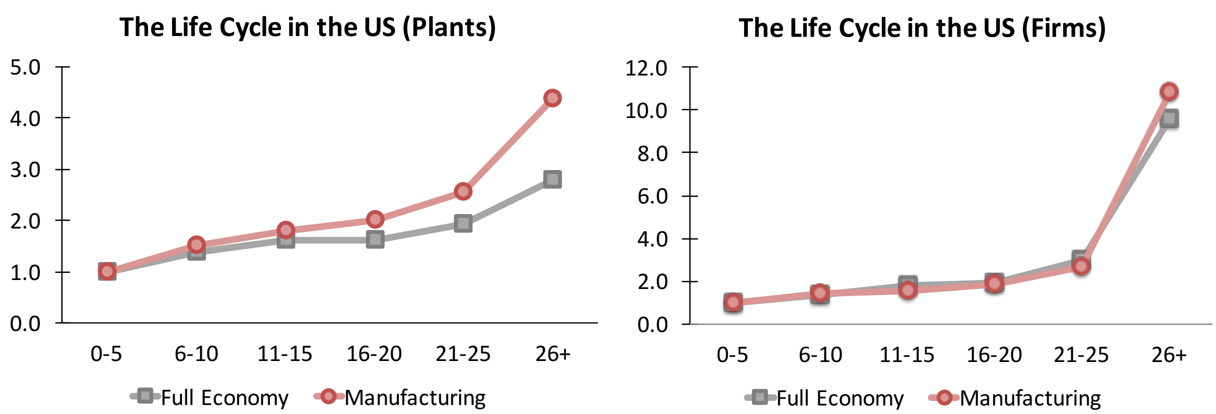
	Firms					Plants			
Size	No.	Avg. Employment	Agg. Share	No. of plants	Exit rate	No.	Avg. Employment	Agg. Share	Exit rate
1-4	86936	2.30	1.65	1.00	13.22	93038	2.31	1.78	16.50
5-9	48178	6.68	2.66	1.00	3.46	54281	6.73	3.02	4.20
10-19	37942	13.80	4.33	1.01	2.66	45803	14.01	5.30	3.10
20-49	32555	30.92	8.31	1.05	2.27	44085	31.90	11.62	2.40
50-99	13516	67.94	7.58	1.21	2.03	21582	71.54	12.75	1.90
100-249	8914	139.90	10.30	1.61	1.59	16476	155.76	21.20	1.00
250-499	3167	280.96	7.35	2.47	0.92	5444	348.72	15.68	0.50
500-999	1720	503.49	7.15	3.94	0.29	2120	677.19	11.86	0.30
1000+	2423	2531.92	50.67	12.68	0.25	984	2068.2	16.81	0.30
Aggregate	235351	51.44	100		6.53	283813	42.66	100	7.3

Notes: This table contains summary statistics for U.S. manufacturing firms and plants in 2012. The data are taken from the BDS.

We now turn to the implied dynamics. Because we focus on cross-sectional data, the information on firm (plant) age is crucial for us. For plants, the definition of age is straightforward.

Birth year is defined as the year a plant first reports positive employment in the LBD. Plant age is computed by taking the difference between the current year of operation and the birth year. Given that the LBD series starts in 1976, the observed age is by construction left censored at 1975. In contrast, firm age is computed from the age of the plants belonging to that particular firm. A firm is assigned an initial age by determining the age of the oldest plant that belongs to the firm at the time of birth. Firm age accumulates with every additional year after that. In Figure OA-1 we show the cross-sectional age-size relationship for plants (left panel) and firms (right panel) in the U.S.

Figure OA-1: Life Cycle of plants and firms in the U.S.



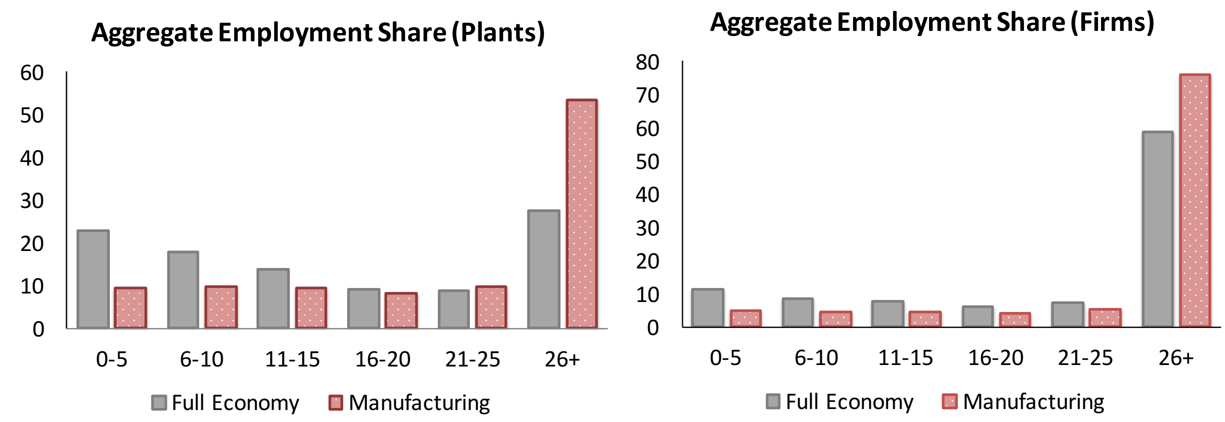
Notes: The figure contains the cross-sectional age-size relationship for plants (left panel) and firms (right panel) in the U.S. The data are taken from the BDS and we focus on the data for 2012. We depict the results for both the manufacturing sector and the entire economy.

Not surprisingly, the life-cycle is much steeper for firms, especially for +26-year-old ones, as firms grow both on the intensive margin at the plant level and the extensive margin of adding plants to their operation.

In Figure OA-2 we show the aggregate employment share of plants and firms of different ages. As suggested by the life-cycle patterns in Figure OA-1, old firms account for the bulk of employment in the U.S. However, the relative importance of old plants/firms is somewhat less pronounced because of exit, i.e., while the average firm/plant grows substantially by age conditional on survival, many firms/plants have already exited by the time they would have been 20 years old. Nevertheless, firms (plants) older than 25 years account for 76% (53%) of employment in the manufacturing sector.

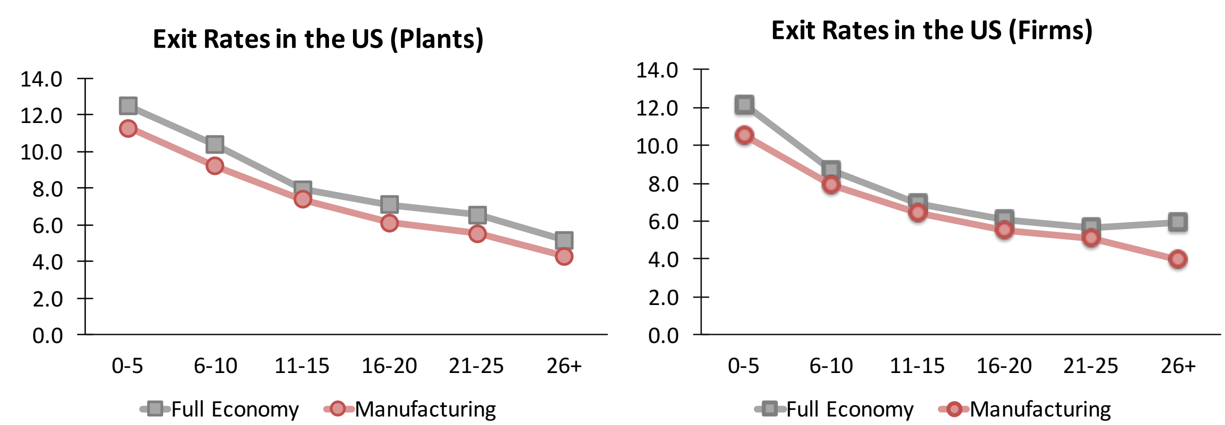
This pattern of exit is depicted in Figure OA-3. There we show annual exit rates for firms and plants as a function of age. The declining exit hazard is very much suggestive of a model of creative destruction, whereby firms and plants grow as they age (conditional on survival) and exit rates are lower for bigger firms/plants.

Figure OA-2: The employment share by age of plants and firms in the U.S.



Notes: The figure contains the aggregate employment share of plants (left panel) and firms (right panel) in the U.S. as a function of age. The data are taken from the BDS and we focus on the data for 2012. We depict the results for both the manufacturing sector and the entire economy.

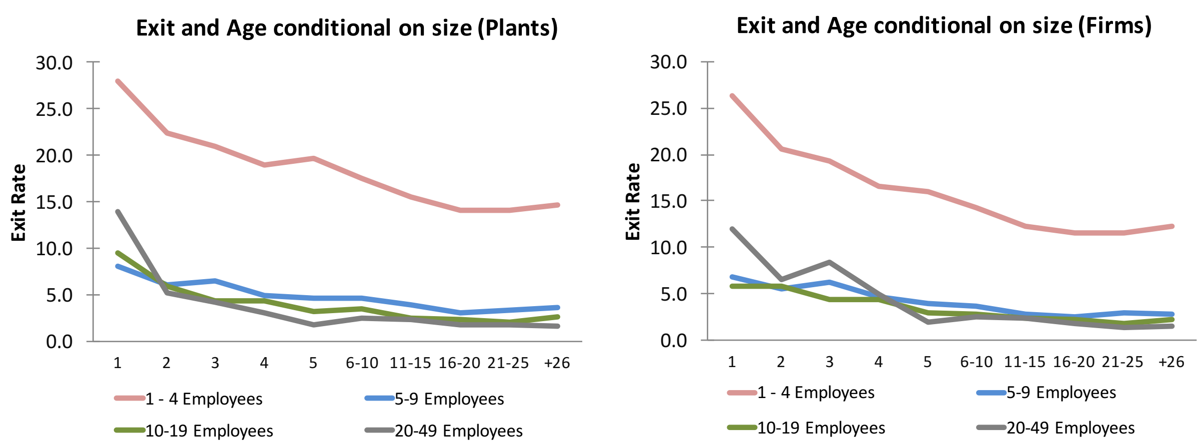
Figure OA-3: The exit rates of plants and firms in the U.S. by age



Notes: The figure contains the exit rates of plants (left panel) and firms (right panel) in the U.S. as a function of age. The data are taken from the BDS and we focus on the data for 2012. We depict the results for both the manufacturing sector and the entire economy.

An important moment for us is the age-specific exit rate conditional on size. It is this moment that will identify the importance of selection. In a model without heterogeneity, size will be a sufficient statistic for future performance, so that age should not predict exit conditional on size. However, if the economy consists of high- and low-type entrepreneurs, old firms are more likely to be composed of high types conditional on size. Hence, the size-specific exit rate by age is monotone in the share of high types by age. In Figure OA-4 we report this schedule for both plants and firms. The data show a large degree of age-dependence (conditional on size). The schedules for small firms and plants look almost identical. This is reassuring because small firms are almost surely single-plant firms, so that a firm-exit will also be a plant-exit and vice versa.

Figure OA-4: Size-dependent exit rates of plants and firms in the U.S. by age



Notes: The figure contains the conditional exit rates by size of plants (left panel) and firms (right panel) in the U.S. as a function of age. The data are taken from the BDS and we focus on the data for 2012. We depict the results for the manufacturing sector.

OA-2.2 Plants in the Indian Manufacturing Sector

In this section we provide more descriptive evidence about the underlying process of firm dynamics in the manufacturing sector in India. Table OA-2 contains descriptive statistics for our sample of Indian manufacturing plants. For comparison, we organize the data in the same way as in the left panel of Table OA-1, which contains the results for manufacturing plants in the U.S. It is clearly seen that the plant-size distribution in India is concentrated on very small firms. The average plant has fewer than 3 employees and more than 50% of aggregate employment is concentrated in plants with at most 4 employees. Such plants account for 93% of all plants in the Indian manufacturing sector.

Figure OA-5 reports the aggregate employment share by age for Indian manufacturing plants and is hence comparable to Figure OA-2 for the U.S.

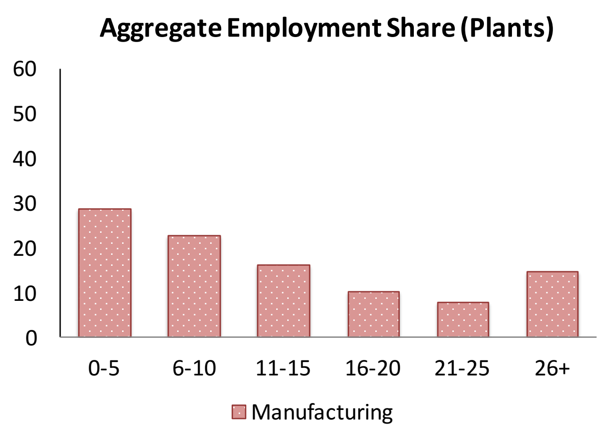
It is clearly seen that the aggregate importance of old firms is very small in India. While firms, that are older than 25 years account for 55% of employment in the U.S., the corresponding number is less than 20% in India. This is a reflection of the shallow life-cycle in India and not of there being fewer old firms in the Indian economy.

Table OA-2: Descriptive Statistics: Indian Micro Data

Size	No.	Avg. Employment	Aggregate Employment Share
1-4	15957296	1.56	54.76
5-9	843091	6.26	11.61
10-19	243868	12.98	6.96
20-49	70834	29.22	4.55
50-99	23242	69.89	3.57
100-249	14898	149.31	4.89
250-499	4701	346.69	3.58
500-999	2283	683.86	3.43
1000+	1232	2452.65	6.65
Aggregate	17161444	2.65	100.00

Notes: This table contains summary statistics for plants in the Indian manufacturing sector in 2010. The data are taken from the ASI and the NSS. To calculate the number of firms, we use the sampling weights provided in the data.

Figure OA-5: The employment share by age of plants in India



Notes: The figure contains the aggregate employment share of manufacturing plants in India as a function of age. The data are taken from the ASI and the NSS and we focus on the data for 2010. We combine the two data sets using the sampling weights provided in the micro data.