American Economic Review 2021, 111(1): 231–275
https://doi.org/10.1257/aer.20180555

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

By Ufuk Akcigit, Harun Alp, and Michael Peters*

Delegating managerial tasks is essential for firm growth. Most firms in developing countries, however, do not hire outside managers but instead rely on family members. In this paper, we ask if this lack of managerial delegation can explain why firms in poor countries are small and whether it has important aggregate consequences. We construct a model of firm growth where entrepreneurs have a fixed time endowment to run their daily operations. As firms grow large, the need to hire outside managers increases. Firms' willingness to expand therefore depends on the ease with which delegation can take place. We calibrate the model to plant-level data from the United States and India. We identify the key parameters of our theory by targeting the experimental evidence on the effect of managerial practices on firm performance from Bloom et al. (2013). We find that inefficiencies in the delegation environment account for 11 percent of the income per capita difference between the United States and India. They also contribute to the small size of Indian producers, but would cause substantially more harm for US firms. The reason is that US firms are larger on average and managerial delegation is especially valuable for large firms, thus making delegation efficiency and other factors affecting firm growth complements. (*JEL* D22, G32, L25, L26, O14)

*Akcigit: University of Chicago, NBER, and CEPR (email: uakcigit@uchicago.edu); Alp: Federal Reserve Board of Governors (email: harun.alp@frb.gov); Peters: Yale University, NBER, and CEPR (email: m.peters@yale.edu). Emi Nakamura was the coeditor for this article. We thank five anonymous referees and the editor for their very valuable comments. We also thank Nick Bloom for sharing the microdata of Bloom et al. (2013), and our discussants Francesco Caselli, John Haltiwanger, Chang-Tai Hsieh, Rasmus Lentz, and Yongs Shin. Chang-Tai Hsieh and Pete Klenow have also kindly shared some of their data with us. We furthermore received very valuable feedback from Abhijit Banerjee, Nick Bloom, Matthew Cook, Jeremy Greenwood, Bill Kerr, Pete Klenow, Chad Jones, Sam Kortum, Robert E. Lucas, Giuseppe Moscarini, Luis Serven, Andrei Shleifer, and Nancy Stokey. We also thank seminar and conference participants at Harvard, MIT, University of Chicago, Stanford, Princeton, Yale, USC, LSE, the Productivity, Development and 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, MN 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. Jeremy Pearce and Lucas Conwell 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. The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or any other person associated with the Federal Reserve System.

†Go to https://doi.org/10.1257/aer.20180555 to visit the article page for additional materials and author disclosure statements.

Managerial delegation is essential for firm growth. In the developed world, many family-owned industrial giants, such as Walmart, The Lego Group, or Ford Motor Co., have managed to expand to hundreds of thousands of employees by relying on professional managers to run their daily operations. In contrast, firms in developing economies often shun outside managers and recruit managers exclusively among family members. Are such cross-country differences in the ease of managerial delegation important determinants of the process of firm growth? Might such limits to delegation allow small and unproductive firms in poor countries to survive because they limit the competitive pressure from more productive producers? And do they have important macroeconomic implications by reducing aggregate productivity and income per capita? In this paper, we answer these questions both theoretically and quantitatively.

To do so, we propose a macroeconomic model of firm dynamics where the need for managerial delegation takes center stage. Firms are run by entrepreneurs, who have the opportunity to increase their productivity in order to expand. Because the entrepreneur's own managerial time is a fixed factor, production features decreasing returns, and marginal profits decrease in firm size. This reduces firms' incentives to grow large. Entrepreneurs can endogenously overcome such limits to their span of control by hiring outside managers. If delegating managerial responsibilities to outside managers is riddled with problems, entrepreneurs have no incentive to invest in productivity growth as they anticipate not being able to efficiently delegate as they grow. Increases in the efficiency of delegation, therefore, raise the returns to grow large and increase aggregate productivity.

Our theory highlights an inherent complementarity between managerial delegation and firm size. Small firms do not consider the fixed managerial human capital of their entrepreneurs a drag on profitability. Only once firms reach a certain size does the entrepreneur's span of control become binding and outside managers valuable. This non-homotheticity, whereby larger firms use outside managers more intensely, implies that frictions in the process of delegation affect the equilibrium distribution of firm size and the process of reallocation in a specific way. Firms with growth potential are hurt if outside managers cannot be employed efficiently and hence reduce their expansion efforts. In contrast, stagnant firms, which never grow beyond a certain size, benefit from such imperfections: they do not hire managers themselves, and they are more likely to survive, because they are shielded from the competition from their dynamic counterparts.

To quantify the importance of this mechanism, we calibrate our model to plant-level microdata from India and the United States. Our quantitative methodology has two main features. First, we allow the structural parameters of our model to be country-specific and calibrate them to the Indian and US data independently. This approach is important to address the identification problem implied by the non-homotheticity of managerial demand: are firms in India small and is managerial delegation rare because delegation is difficult? Or do other frictions in India keep firms small and hence reduce the demand for outside managers in equilibrium? Our calibration strategy explicitly recognizes that firms in India might face higher barriers to growth (e.g., due to capital market inefficiencies or distortionary regulation), that entry costs might be higher (e.g., due to frictions in the access to start-up capital), or that many firms in India might be "subsistence entrepreneurs," who may simply lack the ability to grow their firms beyond a certain size. By allowing these features of the environment to be arbitrarily correlated with the efficiency of delegation, we refrain from attributing all differences between the United States and India to our mechanism of interest.

Second, we use well-identified micro-estimates as "identified moments" to calibrate our structural model (Nakamura and Steinsson 2018). Specifically, we exploit variation in managerial practices based on the randomized experiment by Bloom et al. (2013) to estimate the production function for managerial inputs via indirect inference.[1] Bloom et al. (2013) provided a randomly selected group of Indian textile companies with management consulting to introduce American-style frontier management practices. They show this intervention increased the profitability among treatment firms: after two years, the firms that benefited from the intervention produced 9 percent more than firms in the control group. By explicitly using this estimated treatment effect as a moment for our structural model, we ensure our model generates the right microeconomic response to the experimental "management" intervention.

Our estimated model reveals stark differences between the United States and India. First, we estimate that the efficiency of delegation is indeed substantially smaller in India: a given manager is only one-half as efficient in an Indian firm, relative to a firm in the United States. Second, we find the share of subsistence firms with little growth potential to be substantially higher in India. Finally, the few Indian firms with the potential to expand are substantially less efficient in doing so relative to the United States. Such differences could, for example, reflect credit market imperfections or distortions to market entry, which prevent firms from expanding or keep innovative firms out of the market entirely.

Taken together, our estimated model implies that the Indian economy suffers from a significant lack of selection, where subsistence producers survive because firms with growth potential have low incentives to expand. Hence, the glut of small firms in India is not merely a reflection of frictions that those small firms face, but rather an indication of a lack of competition stemming from larger firms. Policies aimed at supporting small firms, for example, micro-finance programs, although potentially desirable for their redistributive properties, could be harmful by reducing the reallocation of resources from small stagnant firms to firms with growth potential.

We then use our calibrated model to quantify the importance of frictions in the delegation process to explain such differences in the process of firm dynamics between the United States and India. This analysis yields two main conclusions. First, we show that frictions to delegating managerial tasks in India are partly responsible for this lack of selection. If Indian firms could use outside managers as efficiently as firms in the United States, their incentives to expand would be higher, and as a consequence aggregate productivity and income per capita would rise. Our estimates imply that such frictions can explain 11 percent of the income per capita difference between the United States and India.

Second, the complementarity of firm size and delegation implies an important interaction between the ease of delegation and other differences between India and

[1] We are very grateful to Nick Bloom and his coauthors for sharing their data with us.

the United States. Although the process of firm dynamics in India does depend on the delegation environment, the implications are modest. We find that an increase in the efficiency of delegation to US standards would increase average firm size by around 4 percent and reduce the employment share of small firms by a similar amount. If, in contrast, US firms could use outside managers only as inefficiently as firms in India, the consequences would be much more severe: average firm size would decline by around 14 percent, and the employment share of small firms would increase by 19 percent. The reason is that managerial delegation and other non-managerial factors that determine firm expansion naturally interact.

Related Literature.—That managerial delegation might be a key determinant of firm dynamics and macroeconomic performance goes back to the early work of Alfred Chandler (Chandler 1990) and Edith Penrose, who argue that managerial resources are essential for firms to expand and that a scarcity of managerial inputs prevents the weeding out of small firms, because "bigger firms have not got around to mopping them up" (Penrose 1959, p. 221). Recently, more systematic evidence for the importance of managerial inputs has accumulated. In particular, managerial practices differ systematically across countries, and firms in developed economies are larger and delegate more managerial tasks to outside managers (Bloom and Van Reenen 2007, 2010; McKenzie and Woodruff 2017).

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. Our theory incorporates limits to firms' span of control, as in Lucas (1978), into a micro-founded model of Schumpeterian growth following Klette and Kortum (2004), which has been shown to provide a tractable and empirically successful theory of firm dynamics (see, e.g., Acemoglu et al. 2018; Akcigit and Kerr 2018; Garcia-Macia, Hsieh, and Klenow 2019; Lentz and Mortensen 2008).[2] By explicitly allowing firms to hire outside managers, our model makes firms' span of control an endogenous variable that is jointly determined with the process of firm dynamics and the equilibrium distribution of firm size.[3]

Frictions in the market for managerial inputs are also highlighted in Caselli and Gennaioli (2013); Powell (2019); Grobovšek (2015); and Bloom, Sadun, and Van Reenen (2016). In contrast to our theory, all of these papers assume firm productivity is exogenous, so no interaction exists between the delegation environment and firm growth. Guner, Parkhomenko, and Ventura (2018); Roys and Seshadri (2014); and Xi (2016) present dynamic models of (managerial) human capital accumulation but do not focus on the implications for firm dynamics. Finally, a large literature studies

[2] As in Aghion and Howitt (1992), firm dynamics are determined through creative destruction, whereby successful firms expand through replacing other producers. See Aghion, Akcigit, and Howitt (2014) for a survey of the Schumpeterian growth literature and Akcigit (2017) for the importance of firm dynamics for the process of economic growth.

[3] An overview of some regularities of the firm size distributions in India, Indonesia, and Mexico is contained in Hsieh and Olken (2014). A large literature explains cross-country differences in allocative efficiency across firms as diagnosed in Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). This literature highlights credit market frictions (Buera, Kaboski, and Shin 2011; Moll 2014; Midrigan and Xu 2014), size-dependent policies (Guner, Ventura, and Xu 2008; Garicano, Lelarge, and Van Reenen 2016; Gourio and Roys 2014), monopolistic market power (Peters 2020), and adjustment costs (Asker, Wexler, and De Loecker 2014). See Hopenhayn (2014) for a synthesis of this literature.

the internal organization of the firm; see, for example, Garicano and Rossi-Hansberg (2015) for a survey. This literature has a much richer micro structure of firms' delegation environment and the substitutability of managerial skills, but does not focus on the resulting properties of firm dynamics.[4]

Our model explicitly allows for heterogeneity in firms' innate growth potential. This heterogeneity is important to formalize the idea that limits to delegation affect the extent to which firms with growth potential replace stagnant, subsistence producers. Ample empirical evidence suggests such heterogeneity to be important. Schoar (2010) and Decker et al. (2014) argue some entrepreneurs are "transformative" and have the necessary skills to expand, whereas "subsistence entrepreneurs" may simply never grow independently of the environment in which they operate. Hurst and Pugsley (2011) provide evidence that many firms in the United States intentionally choose to remain small. In the context of developing countries, Banerjee et al. (2015) and de Mel, McKenzie, and Woodruff (2008) stress the importance of persistent differences in growth potential. On the theoretical side, Luttmer (2011) and Lentz and Mortensen (2016) argue models without heterogeneity in growth potential are unable to explain the very rapid growth of a subset of US firms.

Finally, on the methodological front, our paper adds to the recent literature in macroeconomics that uses well-identified microeconomic estimates to identify structural models (Nakamura and Steinsson 2018). Recent examples in the literature on growth and development are Lagakos, Mobarak, and Waugh (2018); Kaboski and Townsend (2011); and Brooks and Donovan (2017). To the best of our knowledge, our paper is the first to use this methodology to estimate a model of firm dynamics.

The remainder of the paper is organized as follows. In Section I, we describe the theoretical model. Section II summarizes the data that we use in our quantitative analysis and discusses the identification of the model. Section III contains the calibration results and discusses a variety of nontargeted moments. In Section IV, we provide our main analysis to quantify the role of the delegation environment for firm dynamics and the aggregate economy. Section V provides various robustness checks of the main quantitative results. Section VI concludes. All proofs and additional details are contained in the online Appendix.

I. Theory

A. *Technology*, *Preferences*, *and Static Allocations*

We consider a continuous-time economy, where a representative household values the consumption of a unique final good, maximizes the stream of per-period utilities $U(C_t) = \ln(C_t)$, and discounts the future at rate ρ. Labor is supplied inelastically, and the members of the household can work as either managers or production workers.

[4] A large empirical literature also studies family firms; see, for example, Bertrand and Schoar (2006). La Porta, Lopez-de-Silanes, and Shleifer (1999) document that family members are regularly controlling shareholders in most countries. Bennedsen et al. (2007) use variation in the gender of the CEO's firstborn child to present causal evidence that family successions hurt performance. In contrast, Mueller and Philippon (2011) argue family ownership has distinct benefits in environments of hostile labor relations.

The final good Y, which we take as the numeraire, is a Cobb-Douglas composite of a unit continuum of varieties,

$$\ln Y_t = \int_0^1 \ln y_{jt}\, dj, \tag{1}$$

and is used for consumption (C_t) and for productivity-enhancing investments by incumbents (R_t) and entrants $(R_{E,t})$. The aggregate resource constraint is therefore given by

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

To save on notation, we drop the time subscript t whenever doing so does not cause any confusion.

Producing the variety y_j requires both production workers and managerial inputs. In particular, we assume managers increase the efficiency of production workers so that firm f can produce good j according to

$$y_{jf} = q_{jf}\phi(e_{jf})\, l_{jf}, \tag{3}$$

where q_{jf} is the firm-product specific efficiency, l_{jf} is the number of production workers employed in producing intermediate good j, e_{jf} denotes the amount of managerial services that firm f allocates toward the production of good j, and $\phi(e_{jf}) \geq 1$ is an increasing function translating managerial services into physical productivity units. Letting w_P denote the equilibrium wage for production workers, the production labor cost of producing one unit of y is therefore given by $MC = w_P/(q\phi(e))$.

Firms can produce multiple products $j \in [0,1]$. In equilibrium, product j will be produced by the firm with the highest productivity q_{jf}. Firm f will therefore produce n_f products if it has the highest productivity in n_f product markets. We denote the producer's (i.e., the highest) productivity of variety j by q_j.

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, the producing firm competes against a competitive fringe of potential producers that can produce variety j at marginal costs w_P/q_j.[5] Because the demand function stemming from (1) has a unitary elasticity, the producing firm engages in limit pricing and sets its price equal to the marginal costs of the competitive fringe. The gross profits after paying for production workers l_j (but before paying any managers the firm might decide to hire) are therefore given by[6]

$$\pi_j(e_j) = p_j y_j - w_P l_j = \left(\frac{\phi(e_j) - 1}{\phi(e_j)}\right)Y. \tag{4}$$

[5] This assumption allows us to abstract from strategic pricing decisions of firms that compete with firms of different productivity. Peters (2020) analyzes a model with strategic pricing. In terms of primitives, the fringe firms have access to the same technology as the leading firm and to a level of managerial services ϕ^{fringe}, which we normalize to unity.

[6] Note that $p_j y_j - w_P l_j = (1 - (w_P l_j)/(p_j y_j))p_j y_j = (1 - (1/\phi(e_j)))Y$ as $p_j = w_P/q_j$ and $p_j y_j = Y$.

Hence, profits from variety j are increasing in the amount of managerial services e_j because managerial inputs increase physical productivity and hence profitability. For analytical convenience, we assume $\phi(e) = 1/(1-e^{\sigma})$, where $e \in [0,1)$ and $\sigma < 1$, which implies

$$\pi(e_j) = e_j^{\sigma} Y, \tag{5}$$

that is, profits are a simple power function of managerial effort parameterized by the elasticity σ.

Managerial resources not only affect firm profitability but also the aggregate allocations. In particular (see online Appendix Section A.1), aggregate output Y is given by

$$Y = Q\mathcal{M}L^P, \tag{6}$$

where $L^P = \int_0^1 l_j dj$ denotes the mass of production workers, $\ln Q = \int_0^1 \ln q_j dj$ is an index of aggregate physical productivity, and $\mathcal{M} = \left(1 - \int_0^1 e_j^{\sigma} dj\right)^{-1}$ summarizes the static effect of managerial services on aggregate productivity. $\mathcal{M}$ is increasing in e_j, because managerial inputs increase labor productivity at the firm level.

B. *Delegation, Span of Control, and Firms' Incentives to Grow Large*

At the heart of our theory is the link between managerial delegation and firms' incentives to grow large. As in Klette and Kortum (2004), firms produce multiple products and grow by expanding into new product markets. In particular, by replacing the current producer of variety j, the firm adds new products to its portfolio and grows in sales, employment, and profits.

Because profits of each product depend directly on the amount of managerial services e, their availability is a key determinant of firms' incentives to expand. We assume firms are run by entrepreneurs, who have a fixed endowment $T < 1$ of managerial efficiency units they provide inelastically to their firms.[7] If an entrepreneur is the current producer in n markets, she will have $e_j = T/n$ units of managerial services per product. That she will want to spread her managerial time equally across all product lines follows directly from the concavity of π. The total profits of a firm of size n are hence,

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

This expression has a simple but important implication: although profits are increasing in the number of products n, they do so at a decreasing rate, because the owner's fixed endowment T limits her span of control, as in Lucas (1978). Firm size n and

[7] Recall that $e < 1$ for $\phi(e) = (1-e^{\sigma})^{-1}$ to be well defined. It can be shown that $T < 1$ is sufficient to ensure this condition is satisfied.

the entrepreneur's managerial endowment T are therefore complements and the marginal return to a unit of additional managerial resources is increasing in firm size:

$$\frac{\partial^2 \Pi(n)}{\partial n \partial T} > 0.$$

Hence, entrepreneurs with larger firms consider their fixed time endowment more of a bottleneck.

Delegation.—To counteract these decreasing returns, the entrepreneur can hire *outside* managers to augment her own endowment of managerial resources. This distinction between entrepreneurs and outside managers is what makes firms' span of control endogenous in our theory: while entrepreneurial human capital T is in fixed supply at the firm level, outside managers can be hired on the market. We assume the entrepreneur's and the managers' human capital are perfect substitutes and that the relative efficiency of outside managers within the firm is given by α. More specifically, if an owner of a firm of size n hires m units of managerial human capital for the production of product j, the total amount of managerial services e is given by

$$e(m) = T/n + \alpha \times m. \tag{7}$$

The parameter α is the key parameter for our analysis. It governs the efficiency of delegating tasks to outside managers, and we therefore refer to it as the *delegation efficiency*. The higher α, the more managerial services a given outside manager generates within the firm.

We want to highlight that α is a parameter of the firm's production structure. Consider, for example, an entrepreneur in India looking to expand. One reason why the entrepreneur might decide to stay small is that the supply of sufficiently talented managers might be low. Another reason might be that the pool of managers may be fine, but he could not prevent them from shirking on the job. The former is about managerial human capital embedded in m. The latter is summarized in the delegation efficiency α.

One can think of many reasons why delegation might be less efficient in a developing economy such as India. First, a large empirical literature argues that the prevalence of efficient management practices, such as quality standards, monitoring, or meritocratic promotions, varies systematically with the level of development (see, e.g., Bloom, Sadun, and Van Reenen 2012 or Bloom and Van Reenen 2010). Second, the efficiency of delegation could depend on the level of technology. For example, if delegation is complementary to IT equipment, technological differences across countries will be a source of variation in α (see, e.g., Bloom, Sadun, and Van Reenen 2009). Finally, α can be interpreted as a reduced-form specification of the prevailing institutional or cultural environment. If, for example, contractual imperfections are severe or the level of trust is low, entrepreneurs might need to spend substantial amounts of their own time monitoring their managerial personnel.[8]

[8] In online Appendix Section A.6, we provide a simple micro-founded example, where a contractual game between the owner and outside managers leads to equation (7) and α is a combination of explicit structural parameters.

We assume outside managers are hired on a spot market at a given wage w_M. This assumption implies that the firm's delegation decision is static. Using (5) and (7), total profits net of managerial payments of a firm of size n are given by

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

The maximization problem in (8) defines both firms' demand for managerial inputs and their final profit function. Two properties are noteworthy. First, the entrepreneur's own managerial input T generates a well-defined extensive margin for managerial hiring. In particular, the firm only hires outside managers if the size of the firm exceeds the endogenous delegation cutoff $n^*(\alpha)$, which is given by

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

where $\omega_M = w_M/Y$. Hence, small firms rely purely on the time of the owner and only start delegating once they reach a size $n > n^*(\alpha)$. The cutoff $n^*(\alpha)$ is decreasing in α, as even small firms utilize outside managers if delegating is easy.

Second, it is easy to verify that the optimal managerial human capital per product $m(n)$, conditional on hiring, that is, if $n > n^*(\alpha)$, is given by

$$m(n) = \left(\frac{\sigma}{\omega_M} \right)^{\frac{1}{1-\sigma}} \alpha^{\frac{\sigma}{1-\sigma}} - \frac{1}{\alpha} \frac{T}{n}. \tag{10}$$

Note first that $m(n)$ is increasing in n; that is, larger firms hire more managers per product to make up for the fact that their own managerial resources are spread thinner and thinner as the firm gets larger. Hence, the demand for outside managerial resources is non-homothetic as larger firms hire managers more intensely. Moreover, the demand for outside managers is increasing in the delegation efficiency α, holding ω_M constant.

Substituting firms' optimal delegation policies into (8) implies firm profits are given by

$$\Pi(n; \alpha) = \tilde{\pi}(n; \alpha) \times Y, \tag{11}$$

where

$$\tilde{\pi}(n; \alpha) = \begin{cases} T^{\sigma} n^{1-\sigma} & \text{if } n < n^*(\alpha) \\ T \frac{\omega_M}{\alpha} + (1-\sigma) \left(\frac{\sigma \alpha}{\omega_M} \right)^{\frac{\sigma}{1-\sigma}} n & \text{if } n \geq n^*(\alpha). \end{cases}$$

This profit function is a crucial object in our analysis, because it summarizes the firm's span of control, that is, the return to expanding into a new product market. Importantly, the possibility of delegation endogenizes the firm's span of control and makes it directly dependent on α.

In panel A of Figure 1, we depict the profit function $\tilde{\pi}(n; \alpha)$ for two different levels of $\alpha^L < \alpha^H$. Small firms are run only by their owner and are subject to diminishing returns: as long as they do not delegate, the marginal profit from producing an additional product is declining; that is, $\tilde{\pi}(n; \alpha)$ is concave in n. Once firms reach the delegation cutoff n^* and start hiring outside managers, however, the profit function

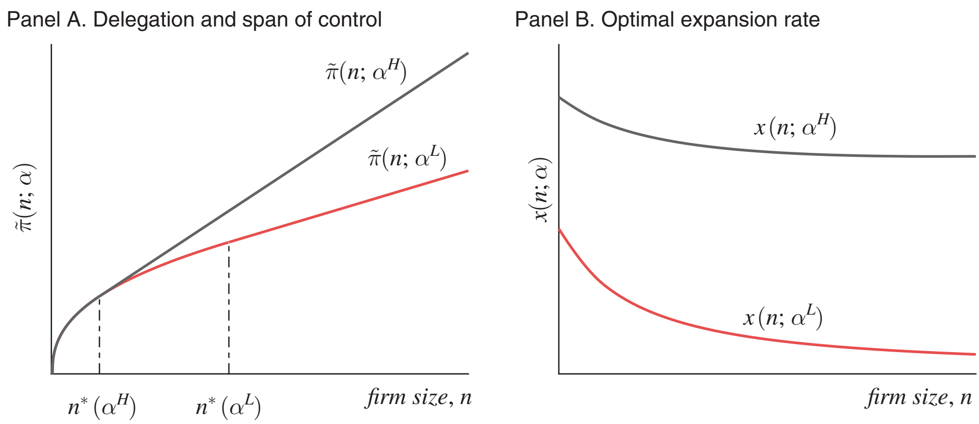


Figure 1. Delegation, Span of Control, and Expansion Incentives

Notes: In panel A, we depict the profit function $\tilde{\pi}(n;\alpha)$ characterized in (11) for α^L and α^H, $\alpha^L < \alpha^H$. In panel B, we depict the optimal expansion schedule $x(n;\alpha)$ in (14).

becomes linear in n. Hence, entrepreneurs overcome their limited span of control by delegating managerial tasks to outside managers.

Now consider an increase in the efficiency of delegation. This increase reduces the delegation cutoff, and smaller firms start to rely on outside managers. Importantly, an increase in α also increases the *slope* of the profit function. This links the delegation environment and the process of firm dynamics: a higher α increases firms' span of control and raises the returns to grow large.

Our model nests two workhorse models in the literature as special cases. When $\alpha = 0$, no scope exists for outside delegation. In that case, $n^* = \infty$, and all firms are subject to diminishing returns, as in Lucas (1978). In contrast, when α is sufficiently large so that $n^* < 1$, every firm delegates, the limited span of control of the owner's own time T is not a bottleneck, and firms' profit functions are linear as in the baseline version of Klette and Kortum (2004). Hence, our model offers a simple framework where the firm's span of control is endogenous and determined in equilibrium.

Firm Expansion.—The efficiency of delegation is a crucial determinant of firms' incentives to expand. For now, we consider the behavior of an individual firm. In Section IC, we embed this structure into a general equilibrium model.

We model firm growth as a stochastic process whereby the firm can choose the rate at which it improves the productivity q of a randomly selected product by $\gamma_t > 1$ and thereby replaces the existing firm. In particular, if a firm with n varieties invests R units of the final good, it expands into a new product line at rate

$$X(R;\theta,n) = \theta[R/Q]^{\zeta} n^{1-\zeta}, \tag{12}$$

where θ, which we refer to as firms' growth potential, determines the efficiency of innovation, $\zeta < 1$ parametrizes the convexity of the expansion cost function, and Q_t

is the productivity index defined in (6).[9] At the same time, each product the firm currently produces is improved upon by other firms at rate τ_t. This rate of creative destruction is, of course, endogenous and determined in equilibrium, but firms take it as given.

To characterize the firm's optimal expansion policy, we need to solve for its value function. The value of a firm with n products, $V_t(n)$, solves the Hamilton-Jacobi-Bellman equation

$$r_t V_t(n) - \dot{V}_t(n) = \Pi_t(n;\alpha) - n\tau_t\left[V_t(n) - V_t(n-1)\right] + \max_X\left\{X\left[V_t(n+1) - V_t(n)\right] - Q_t n^{\frac{\zeta-1}{\zeta}}\left[\frac{X}{\theta}\right]^{\frac{1}{\zeta}}\right\}, \tag{13}$$

where $\dot{V}_t \equiv \partial V_t/\partial t$. The right-hand side of (13) consists of three parts. First, the firm earns the flow profits $\Pi_t(n;\alpha)$ given in (11). Second, the firm might lose one of its products to other firms, which occurs at the endogenous rate of creative destruction $n\tau_t$ (because each product gets replaced at rate τ_t). Finally, the value function incorporates the option value of expansion: with flow rate X, the firm expands into a new market and experiences a capital gain of $V_t(n+1) - V_t(n)$. The associated costs of expanding into a new market stem from (12). Note the function V_t directly depends on the delegation efficiency α via the profit function.

This value function implicitly defines firms' optimal rate of expansion and productivity growth. Letting $x \equiv X/n$ denote the expansion intensity, optimality requires that

$$x_t(n;\alpha) = \theta^{\frac{1}{1-\zeta}}\zeta^{\frac{\zeta}{1-\zeta}} \times \left(\frac{V_t(n+1) - V_t(n)}{Q_t}\right)^{\frac{\zeta}{1-\zeta}}. \tag{14}$$

Naturally, the incentives to expand depend on the *marginal* return to $V_t(n+1) - V_t(n)$. This marginal return is what links firms' innovation incentives to the ease of delegation. In equation (11) and panel A of Figure 1, we showed that α determines 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, α also determines the slope of the value function and hence the optimal innovation rate for firms of different sizes.

In panel B of Figure 1, we depict the optimal innovation rate $x(n,\alpha)$. The concavity of the profit and value function implies firms' expansion incentives are declining in size. An increase in α affects this schedule in two ways. First, an increase in delegation efficiency shifts the whole expansion schedule upward. Intuitively, if firms anticipate being able to hire outside managers more efficiently once they reach the delegation cutoff n^*, their incentives to expand will already be higher today. Similarly, firms that are already delegating also increase their expansion efforts as their profitability increases. Secondly, innovation incentives increase more for

[9] Because we denote innovation costs in terms of the final good, the scaling variable Q is required to keep the model stationary. We also assume firms' innovation costs depend on the number of varieties n to generate deviations from Gibrat's law solely through incomplete delegation. In particular, if the profit function in (11) were linear, the specification in (12) would imply that firm growth is independent of size.

larger firms, so that the schedule $x(n;\alpha)$ becomes flatter. Hence, improvements in the delegation environment are particularly important for large firms, which rely heavily on outside managers.

C. *Firm Dynamics and Delegation in General Equilibrium*

To determine the aggregate effects of the delegation environment, we now embed this model of firm growth into a general equilibrium model of firm dynamics. At each point in time there is a set of existing firms whose innovation rates are given by (14), and a set of potential entrants that enter the economy by improving upon existing producers.

Firm Heterogeneity.—We explicitly allow firms to be heterogeneous in their growth potential. Formally, we assume firms differ in their innovation efficiency θ and can be either *transformative* (high, θ_H) or *subsistence* (low, θ_L) types. A firm's type is persistent and determined upon entry. Each new entrant draws a firm type $\theta \in \{\theta_H, \theta_L\}$ from a Bernoulli distribution, where

$$\theta = \begin{cases} \theta_H & \text{with probability } \delta \\ \theta_L & \text{with probability } 1-\delta. \end{cases} \tag{15}$$

To capture the existence of subsistence entrepreneurs, we assume $\theta_L = 0$; that is, low-type firms are entirely stagnant. This polar case is conceptually useful because the sole difference in firm dynamics across countries then stems from the innovation incentives for high types: the high types' appetite for expansion is what determines the degree of selection, that is, how long it takes for low-type firms to be replaced.

In addition, we also allow firms to potentially differ in the rate at which they *lose* products due to differences in their reputation, customer loyalty, or organizational capital. Letting τ_H and τ_L be the rates at which high- and low-type firms lose a given product to other firms (both of which will be determined in equilibrium), we assume $\tau_L = \beta\tau_H$. 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. The parameter β is one of our structural parameters that we calibrate from the data. Allowing for $\beta \neq 1$ is not conceptually important; we introduce it mostly for quantitative reasons.

To summarize, the behavior of high types is described by the optimal expansion rate in (14) and the value function in (13) (hereafter denoted by $V_t^H(n)$). Subsistence entrepreneurs, in contrast, never innovate and hence never grow beyond a single product; they exit at rate $\tau_{L,t}$. Their value function is therefore simply given by

$$r_t V_t^L - \dot{V}_t^L = \Pi_t(1;\alpha) - \tau_{L,t} V_t^L. \tag{16}$$

Entry.—A unit mass of potential entrants attempts to enter the economy at any point in time. They use a similar innovation technology as incumbent firms, where the flow rate of entry z is related to the spending on entry efforts R_E according to $z = \theta_E [R_E/Q]^{\zeta}$. Entrants enter the economy with a single, randomly selected

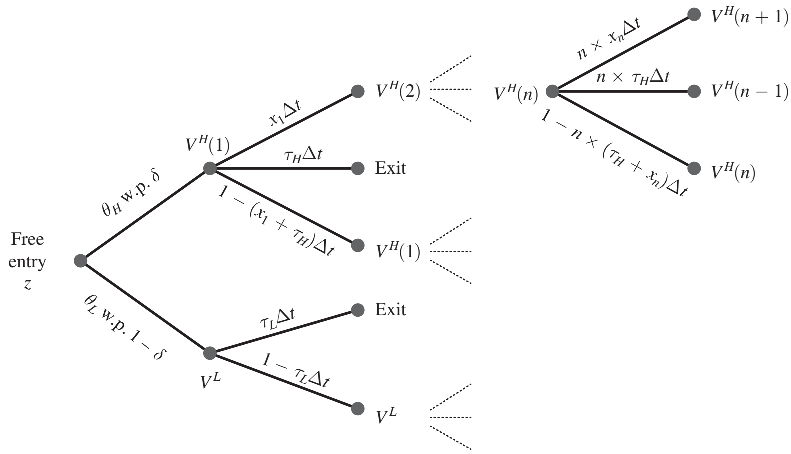


FIGURE 2. LIFE-CYCLE DYNAMICS

product. Given that an entrant becomes a high-type with probability δ, the equilibrium entry flow is given by

$$(17) \qquad z_t(\alpha) = \arg\max_z \left\{ z\left[\delta V_t^H(1) + (1-\delta)\,V_t^L\right] - Q_t \theta_E^{-\frac{1}{\zeta}} z^{\frac{1}{\zeta}} \right\}$$
$$= \theta_E^{\frac{1}{1-\zeta}} \zeta^{\frac{\zeta}{1-\zeta}} \left[\frac{\delta V_t^H(1) + (1-\delta)\,V_t^L}{Q_t}\right]^{\frac{\zeta}{1-\zeta}}.$$

Note the equilibrium entry flow depends on the delegation environment α through firms' value function.

Figure 2 provides an overview of the life-cycle dynamics in our model. Firms enter the economy with a single product and are either transformative, high-type entrepreneurs (with probability δ) or subsistence, low-type entrepreneurs (with probability $1-\delta$). The corresponding value functions are $V^H(1)$ and V^L. Within the next time interval Δt, high-type firms either expand (with probability $x_1\Delta t$), lose their only product and exit (with probability $\tau_H\Delta t$), or remain a one-product firm. In contrast, low-type firms never expand, but instead either exit (with probability $\tau_L\Delta t$) or remain in the economy by serving their initial market.

Delegation Efficiency and the Firm Size Distribution.—The equilibrium firm size distribution is endogenously determined from firms' expansion and entry incentives and hence depends on the delegation environment α. Let F_{nt}^H be the mass of high-type producers with n products, and let F_t^L be the mass of low-type producers (all of which have a single product). In a stationary equilibrium, these objects are constant and have simple expressions. In particular, as we show in online Appendix Section A.2, they are given by

$$(18) \qquad F_n^H(\alpha) = \frac{\delta z(\alpha)}{n x(n;\alpha)} \prod_{j=1}^{n} \left(\frac{x(j;\alpha)}{\tau_H(\alpha)}\right) \quad \text{and} \quad F^L(\alpha) = \frac{(1-\delta) z(\alpha)}{\tau_L(\alpha)}.$$

These expressions follow directly from the flow equations of the firm size distribution. Consider, for example, the case of F^L. Because subsistence firms exit the economy at rate τ_L and $z(1-\delta)$ subsistence entrepreneurs enter each instant, the equilibrium mass of low-type firms is given by $(1-\delta)z/\tau_L$ as in (18). Furthermore, the aggregate rate of creative destruction is given by

$$\tau(\alpha) = \sum_{n=1}^{\infty} nx(n;\alpha)\,F_n^H(\alpha) + z(\alpha), \tag{19}$$

because existing producers get replaced both by other incumbent firms and new entrants. Equations (18) and (19) fully determine the equilibrium firm size distribution as a function of $x_t(n;\alpha)$ and $z_t(\alpha)$ because $\tau_L = \beta\tau_H$ and consistency requires that $\tau = \tau_H(1-F^L) + \tau_L F^L$.[10]

The expressions in (18) are useful to build intuition for how managerial delegation shapes the distribution of firm size. Recall that firm sales are proportional to the number of products n. The aggregate share of sales of firms with $n+1$ products relative to firms with n products is given by

$$\frac{(n+1)\,F_{n+1}^H}{n\,F_n^H} = \frac{x(n;\alpha)}{\tau_H(\alpha)}. \tag{20}$$

Hence, the relative importance of large producers is directly determined by the size-dependent innovation schedule $x(n;\alpha)$: the faster $x(n;\alpha)$ is declining in n, the smaller the aggregate importance of large firms. Panel B of Figure 1 therefore already suggests the link between delegation and the endogenous firm size distribution. If α is low, firms' span of control is a bottleneck for large firms, and the optimal innovation rate $x(n;\alpha)$ declines steeply in size n, as does the aggregate importance of large firms. Improvements in the efficiency of delegation therefore induce reallocation toward large producers. Similarly, the expression for the equilibrium mass of subsistence firms F^L shows why inefficiencies in the process of delegation reduce selection and keep low-type firms alive: by harming large firms more than small firms, they reduce creative destruction more than the entry rate. Environments where delegation is difficult therefore enable low-type firms to survive. In our quantitative analysis, we show these intuitions carry through once we take general equilibrium effects into account.

Creative Destruction and Aggregate Growth.—The rate of creative destruction is also the driver of aggregate growth in our economy. Recall that each successful innovation increases productivity by the step size γ_t. Because the rate of creative destruction is the rate at which such innovations take place, the aggregate growth rate of the productivity index Q_t is given by (see online Appendix Section A.3)

$$g_t(\alpha) \equiv \frac{\dot{Q}_t}{Q_t} = \ln(\gamma_t) \times \tau_t(\alpha). \tag{21}$$

This expression highlights the relationship between delegation and aggregate growth. In our model, more efficient delegation increases aggregate growth

[10] Note F_t^L is the share of products that are produced by subsistence entrepreneurs as they produce one product each.

through its effect on expansion and entry and hence creative destruction. Whether such increases in the rate of growth are persistent, depends on the behavior of the step size γ_t. As far as the process of firm dynamics is concerned, we do not have to take a stand on γ_t, because our model permits a stationary firm-size distribution even if the step size γ_t varies over time; see online Appendix Section A.5, where we prove this property formally. However, to quantify the effect of delegation on long-run productivity differences, we consider a model where γ_t is endogenous and the long-run distribution of income across countries is stationary. Hence, differences in α between the United States and India will result in level differences, not growth differences (see Section IV).

D. *The Labor Market Equilibrium for Outside Managers*

To complete the characterization of the equilibrium, we need to specify the supply and demand of managerial inputs. The demand for outside managers results from firms' optimal hiring decisions. Because of the non-homotheticity of managerial demand, larger firms delegate more intensely, and the aggregate demand for managerial inputs depends on the endogenous firm size distribution. Using the optimal hiring rule in (10), a firm with $n \geq n^*$ products hires a total of $nm(n)$ managerial efficiency units. The demand for outside managers, H^{OM}, is therefore given by

$$H^{OM} = \sum_{n=1}^{\infty} \mathbf{1}(n \geq n^*) m(n) n F_n(\alpha) \tag{22}$$

$$= \sum_{n=1}^{\infty} \underbrace{\mathbf{1}(n \geq n^*)\left(\left(\frac{\sigma}{w_M/Y}\right)^{\frac{1}{1-\sigma}} \alpha^{\frac{\sigma}{1-\sigma}} n - \frac{T}{\alpha}\right)}_{\text{Managerial demand given firm size}} \underbrace{F_n(\alpha)}_{\text{Effect of FSD}},$$

where $F_n = F_n^H + \mathbf{1}(n = 1) F^L$. This expression highlights two important determinants of managerial demand. Holding the firm size distribution constant, aggregate demand is increasing in α. In addition, because managerial demand is non-homothetic, the firm size distribution $F_n(\alpha)$ itself also affects managerial demand directly: if firms are small, outside managers are in low demand because small firms can be run by their owners. This dependence on $F_n(\alpha)$ highlights an important identification challenge that our empirical strategy has to address: do we see few outside managers in India because delegation is difficult? Or do other frictions keep Indian firms small, and hence no managers are required?

To model the supply of managerial workers, we assume each individual is endowed with a single efficiency unit of production labor and h units of managerial human capital, distributed according to $G(h)$. Individuals make their occupational choice to maximize total earnings; that is, individual i works as an outside manager if $h_i w_M > w_P$. Labor market clearing therefore requires that

$$H^{OM} = \int_{h \geq \frac{w_P}{w_M}} h g(h)\, dh, \tag{23}$$

where $g(h)$ is the density associated with $G(h)$.

In our application, we assume h is drawn from a Pareto distribution, namely $G(h) = 1 - (((\vartheta - 1)/\vartheta)\,\mu_M)^{\vartheta} \times h^{-\vartheta}$. Here, μ_M parametrizes the average level of managerial skills, and $\vartheta > 1$ governs the heterogeneity in managerial talent. Using this functional form, the labor market clearing condition in (23) is given by

$$H^{OM} = \left(\frac{\vartheta - 1}{\vartheta}\mu_M\right)^{\vartheta}\left(\frac{w_M}{w_P}\right)^{\vartheta - 1}\frac{\vartheta}{\vartheta - 1}. \tag{24}$$

Note the supply of outside managers is increasing in the relative wage with an elasticity of $\vartheta - 1$. Moreover, holding relative wages fixed, the supply of managerial skills is increasing in the average level of managerial human capital μ_M.

An equilibrium in our economy is then defined in the following way.

DEFINITION 1: *Consider the environment described above. A dynamic equilibrium path is characterized by a time path of*

$$\left[p_{jt}, y_{jt}, \left\{V_t^H(n)\right\}_{n=1}^{\infty}, V_t^L, \left\{x_t(n)\right\}_{n=1}^{\infty}, z_t, w_{t,M}, w_{t,P}, \left\{F_{nt}^H\right\}_{n=1}^{\infty}, F_t^L, r_t, g_t\right]_{t=0}^{\infty},$$

such that (i) p_{jt} *and* y_{jt} *maximize monopoly profits in* (4), (ii) *the value functions* $V_t^H(n)$ *and* V_t^L *are given by* (13) *and* (16), (iii) *the innovation rates* $x_t(n)$ *are optimal and given in* (14), (iv) *the entry rate* z_t *satisfies* (17), (v) $w_{t,P}$ *and* $w_{t,M}$ *clear the labor market for production and managerial labor*, (vi) *the mass of firms of each size* $\left[F_{nt}^H, F_t^L\right]$ *are consistent with the flow equations in online Appendix Section A.2*, (vii) *the interest rate* r_t *satisfies the household's Euler equation*, *and* $(viii)$ *the aggregate productivity growth rate is consistent with* (21).

E. *Taking Stock*

We have developed a theory to link the efficiency of delegation to firms' growth incentives and hence the process of firm dynamics and the equilibrium firm size distribution. At the heart of our model is the insight that a higher efficiency of delegation endogenously increases firms' span of control and hence their incentives to grow large.

To summarize the effects of an increase in delegation efficiency α, consider Figure 3, where we depict the qualitative relationships between α and various equilibrium outcomes.[11] Panel A shows a positive relationship between delegation efficiency and firms' life-cycle growth. This follows directly from the resulting increase in firms' expansion incentives, in particular for large firms. This faster growth at the firm level shifts the firm-size distribution to the right so that the employment share of small firms declines (panel B). These changes at the firm level are accompanied by changes in the labor market. In particular, the employment share of outside managers is increasing

[11] Although these relationships stem from our quantitative model and we currently do not have an analytical proof, we have yet to find a counterexample. Hence, we suspect these comparative static results hold true regardless of the particular parametrization of the model.

Figure 3. Taking Stock: Delegation, Selection, and Firm Dynamics

Notes: The figure summarizes the qualitative implications of changes in the delegation efficiency α for firms' life-cycle growth (panel A), the employment share of small firms (panel B), the managerial employment share (panel C), and the equilibrium share of low-type firms (panel D).

in α both because firms' demand for managers increases and because the firm size distribution shifts to the right, which further increases managerial demand, because large firms are manager intensive (panel C). Finally, because firms are heterogeneous in their growth potential, an increase in α will also be accompanied by selection. Because subsistence entrepreneurs are small in equilibrium, they do not benefit from the opportunity to hire managers. In contrast, they *lose* from improvements in delegation efficiency because they are less likely to survive (panel D).

These patterns are qualitatively consistent with stylized facts on firm dynamics in poor countries where firms are small and do not grow, subsistence producers are abundant, and outside managers are rare. Importantly, the glut of small, stagnant firms in poor countries might not solely reflect frictions these firms face, but may also result from more productive firms not being able to overcome limits to their span of control. Improvements in the efficiency of delegation enable firms with growth potential to overcome these decreasing returns and speed up the aggregate selection process. In the remainder of this paper, we analyze whether this mechanism can quantitatively account for the observed differences in the firm size distribution between the United States and India and whether it has important implications for differences in income per capita.

II. Data and Calibration Strategy

A. *Data*

In this section we briefly describe the main data sources. A detailed description is contained in online Appendix Section B.1.

Establishment-Level Data for the United States and India.—We calibrate our model to data for the manufacturing sector of the United States and India. For the United States we rely on publicly available data for the population of manufacturing plants from the Business Dynamics Statistics (BDS). The BDS is provided by the US Census Bureau and compiled from the Longitudinal Business Database (LBD), which provides data on employment and age for each establishment with paid employees (US Census Bureau, Center for Economic Studies 2016). We focus on the data from 2012.

Analyzing data for the manufacturing sector in India is less straightforward, because no single database provides this information. To capture the entirety of the manufacturing sector, we follow Hsieh and Klenow (2014) and Hsieh and Olken (2014) and combine the Annual Survey of Industries (ASI, MOSPI 2013) and the survey of the unorganized manufacturing sector from the National Sample Survey (NSS, MOSPI 2012). The ASI focuses on the formal sector and covers all establishments employing 10 or more workers using electric power or employing 20 or more workers without electric power. The NSS, every five years, surveys a random sample of the population of manufacturing establishments outside the sampling frame of the ASI. Hence, the firms in the NSS are decidedly smaller and mostly informal: more than 80 percent of plants have at most 2 employees and less than 1 percent have more than 15 employees (see online Appendix Table 1, where we report the firm size distribution in the NSS). 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 datasets are available.

For our analysis, we treat this union of the ASI and NSS data as representing the population of manufacturing firms in India. To provide direct evidence for the representativeness of these data, we compared them with the Indian Economic Census, which is a complete count of all economic units in India. As we show in online Appendix Section B.1, the cross-sectional firm size distributions of the ASI/NSS sample and the Economic Census are very similar. We cannot rely on the Economic Census for our main analysis, because it does not contain information on firm age and hence cannot be used to estimate the employment life cycle or to measure firm entry.

Table 1 contains some basic descriptive statistics about the distribution of establishment size in the United States and India.[12] Expectedly, the importance of large firms differs enormously. In the United States, two-thirds of manufacturing

[12] Recently, Rotemberg and White (2017) argued the data in the United States and India differ in terms of data cleaning strategies. These concerns are less relevant for our study because we only rely on sample averages of the reported employment data and do not utilize information on any higher moments, which are important for the measurement of misallocation. We did recalculate all estimation moments after dropping firms in the top and bottom 2 percent of the employment distribution (both in the population of firms and conditional on age) and found this decision had little effect on our analysis.

TABLE 1—ESTABLISHMENT SIZE AND MANAGERIAL EMPLOYMENT IN THE UNITED STATES AND INDIA

	Establishment size					
	Average employment	1–4 employees		≥100 employees		Employment share of outside managers
		Share	Employment share	Share	Employment share	
United States	42.7	32.8%	1.8%	8.8%	65.5%	12.5%
India	2.7	93.0%	54.8%	0.1%	18.6%	1.65%

Notes: The table contains summary statistics from the firm size distribution in the United States and India. The US data come from the BDS in 2012, and the data for India come from the NSS and ASI in 2010. In the last column, we report the share of outside managers, that is, all workers who are classified as managers according to the occupation classification ISCO and who are hired as wage workers. These data stem from IPUMS.

employment is concentrated in establishments with at least 100 employees, and only one-third of the establishments have fewer than 4 employees. In India, more than 9 out of 10 establishments have fewer than 4 employees, and they account for more than one-half of aggregate employment. Because the Indian data are collected at the level of the establishment, our benchmark analysis focuses on individual establishments. We conduct robustness checks using firm-level data for the United States in Section V.

Data on Managerial Employment.—To measure managerial employment, we rely on national census data provided by the IPUMS project (Minnesota Population Center 2019). 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 United States. Our theory stresses the importance of *outside* managers. We, therefore, classify employees as managers if they are assigned the occupational code "Legislator, Senior official, and manager" *and* they are hired as wage workers instead of being, for example, unpaid family members or the owner themselves. As shown in the last column of Table 1, in the United States roughly 12.5 percent of employees satisfy this criterion. In India, less than 2 percent are employed as outside managers.

Insisting on outside managers is important. In the United States, roughly 14 percent of the labor force is classified as managers according to their occupational code. The majority, namely 91 percent, are wage workers and hence outside managers in the sense of our theory. By contrast, in India only 14 percent of individuals working in a managerial occupation are wage workers. The remainder are either entrepreneurs themselves or unpaid family members. Hence, Indian firms acquire managerial services mostly from their owners or close family members. This pattern is very much the exception in the United States.

An important implication of our model is that firms' demand for outside managers is non-homothetic: larger firms have higher managerial employment shares. In Table 2, we show such non-homotheticities to be the norm in the Indian firm-level data.[13] Whereas firms with 1–4 employees have essentially no managerial personnel, firms

[13] The definition of outside managers is similar between the firm-level data and the data from IPUMS. The firm-level data have an employment category "supervisory and managerial staff." This category contains everyone who holds positions of supervision and management and who are working proprietors and managers when paid a regular salary. This category is distinct from the category "working proprietors," that comprises all owners who are actively engaged in the work of the enterprise and all unpaid working proprietors. We use the managerial

Table 2—Non-Homothetic Managerial Demand in India

	Number of employees							Full sample
	1–4	5–9	10–19	20–49	50–99	100–999	1,000+	
Share of managers	0.002	0.017	0.043	0.077	0.079	0.101	0.147	0.029

Notes: The table reports the share of managerial employment among firms of a given size (columns 1–7) and for the aggregate economy (last column). The data combine the NSS data from 1995 and the ASI data from 1999. 1995 is the only year where we observe managerial hiring in the NSS data, and 1999 is the closest year for which we have access to the ASI data.

with more than 100 employees have managerial employment shares exceeding 10 percent. The aggregate managerial share as measured from the firm-level data is 2.9 percent, which is reasonably close to the 1.65 percent reported in IPUMS. Below, we show the predictions of our model are also quantitatively in line with Table 2.

Although measuring such non-homotheticities from the firm-level data is natural, doing so has the disadvantage that we cannot report Table 2 for the United States (because the BDS data do not have information on managerial employment). In online Appendix Section B.1 (see in particular Figure 1), we use data from the Current Population Survey (CPS), which shows managerial hiring is also non-homothetic in the United States (Flood et al. 2020). In addition, because the IPUMS data for India (but not for the United States) contain information on the size of the establishment individuals work in, we also corroborate the results reported in Table 2 using the data from IPUMS.

B. *Identification and Calibration*

Our model has 12 structural parameters:

$$\Omega \equiv \left\{ \underbrace{\alpha, \sigma, T, \mu_M, \vartheta}_{\text{Management}}, \underbrace{\theta, \theta_E, \zeta, \delta, \beta}_{\text{Firm dynamics}}, \underbrace{\gamma_t, \rho}_{\text{Macro}} \right\}.$$

Five parameters are directly related to the demand for and supply of managerial services: the delegation efficiency (α), the managerial output elasticity (σ), the owners' own human capital (T), and the distribution of managerial skills (μ_M and ϑ). The process of firm dynamics is captured by the expansion and entry efficiencies (θ and θ_E), the convexity of the cost function (ζ), the share of high-type entrants (δ), and the difference in type-specific creative destruction rates (β). Finally, the remaining "macro" parameters include the innovation step size (γ_t) and the discount rate (ρ).

As highlighted above, we estimate most of these parameters separately for the United States and India. We restrict three parameters to be the same across countries: ρ, ζ, and ϑ. We fix ρ and ζ exogenously and calibrate the remaining parameters by minimizing the distance between several empirical moments and

employment share from IPUMS as our main calibration target to ensure the classification is consistent between the United States and India.

their model counterparts.[14] In particular, let M^E denote the vector of S empirical moments and let $M(\Omega)$ denote the vector of model-simulated moments. We then chose Ω to minimize the absolute relative deviation between the model and data; that is, we solve

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

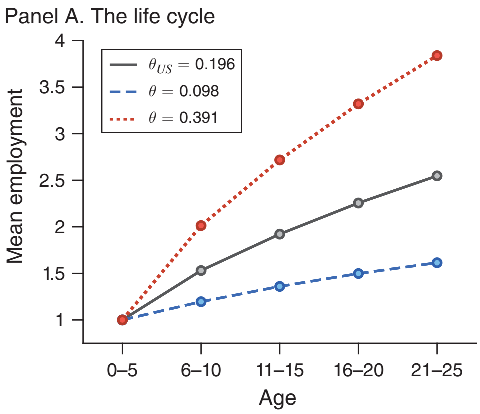
Even though our parameters are calibrated jointly, below we provide a heuristic description of the relationship between the parameters and specific moments. In online Appendix Section B.2, we give a more formal identification discussion and verify these relationships numerically using a sensitivity matrix, where we report the elasticity of each moment used in the internal calibration with respect to the parameters of the model (see online Appendix Table 5).

Note we allow the innovation step size γ_t to be country-specific and time-varying. In particular, we allow for the Indian economy to be along a transition path; that is, catching-up with the United States. Concerning the firm size distributions, we estimate the parameters under the assumption that the distributions are stationary. As we show formally in online Appendix Section A.5, our model implies the firm-size distribution will remain stationary during the transition, that is, despite the fact that the aggregate economy has not yet reached a BGP.[15] We can therefore calibrate all parameters independently of γ_t. In Section IVB, we describe in detail how we discipline the evolution of γ_t.

Firm Dynamics: Identifying θ, δ, β, and θ_E.—The expansion efficiency θ is mostly identified from the profile of firms' life-cycle growth. This is seen in panel A of Figure 4, where we depict average employment by age for different values of θ, holding all other parameters fixed. The higher θ, the faster firms grow conditional on survival. To identify the share of high-type producers δ, we focus on the age profile of exit rates *conditional* on firm size. Without type heterogeneity, the likelihood of exit would be independent of age conditional on size. In the data, however, such conditional exit rates are strongly decreasing in firm age (see, e.g., Haltiwanger, Jarmin, and Miranda 2013). Through the lens of our model, this pattern is rationalized through endogenous selection, whereby the share of low-type firms within a given cohort declines as the cohort ages. This is shown in panel B of Figure 4, where we display the exit rate of small firms by age for different values of δ. Without any heterogeneity, that is, $\delta = 1$, the conditional exit hazard is flat. The parameter β, which determines how quickly low-type firms lose market share, is identified from the aggregate employment share of old firms. Intuitively, because high-type firms are older on average, the aggregate size of old cohorts is informative about this parameter. Finally, the entry efficiency θ_E is identified from the aggregate entry rate.

[14] Because 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, whose estimates imply a quadratic cost function, namely, $\zeta = 0.5$. See Akcigit and Kerr (2018) and Acemoglu et al. (2018), who discuss this evidence in more detail. In Section V, we provide a battery of robustness checks. We set the discount rate ρ equal to 5 percent.

[15] Empirically, the firm size distribution in India is relatively stable over time, despite the fast convergence in income per capita (see online Appendix Section B.6).



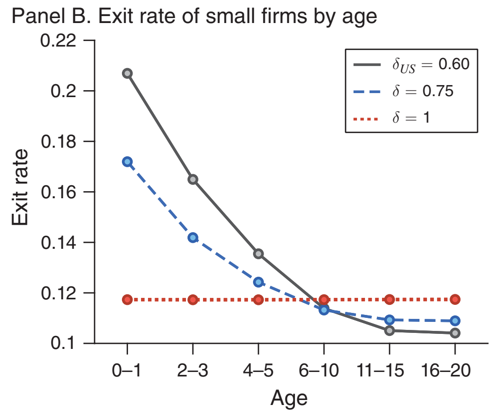


Figure 4. Identification of δ and θ

Notes: Panel A shows the employment life cycle, that is, average employment by age, for different values of θ. Panel B shows the exit rate of one-product firms by age for different values of δ. The black line depicts the US calibration (i.e., $\theta_{US} = 0.196$ in panel A and $\delta_{US} = 0.60$ in panel B). The other lines are obtained by varying θ (panel A) or δ (panel B) while keeping the rest of the parameters constant.

Identifying the Delegation Efficiency α.—The delegation efficiency α is a crucial parameter of our analysis. Because α directly affects firms' managerial demand, we aim to identify it from the aggregate employment share of outside managers. Doing so, however, requires us to address an important identification problem. Because the share of managers is increasing in firm size, the firm size distribution directly affects the aggregate managerial employment share. For example, consider Figure 5, where we plot the managerial employment share by firm size and the employment distribution in India from our calibrated model. Holding α constant, the managerial share is higher for larger firms. More importantly, holding firm size fixed, the equilibrium managerial share is increasing in α. Because the aggregate managerial share is the integral of the firm level managerial shares with respect to the employment distribution, we have to distinguish whether managerial delegation in India is rare because delegating is difficult or whether other frictions keep Indian firms small and hence reduce the share of outside managers in the aggregate.

To credibly identify the efficiency of delegation α, we therefore need to simultaneously match the aggregate managerial employment share and the firm size distribution. Our model and calibration strategy allows us to do so. In particular, recall that the equilibrium firm size distribution is determined from firms' expansion schedules x_n and the entry rate z (see (18) and (19)). And by allowing the fundamental determinants of x_n and z, namely, the firm dynamics parameters θ, δ, β, and θ_E, to vary between the United States and India in an unrestricted way, our calibration can match the firm size distribution using these parameters and identify α from the residual variation in managerial employment shares between the United States and India.[16]

[16] Differences in high types' growth potential θ could, in a reduced-form way, capture differences in capital market efficiency that prevent Indian firms from investing (see, e.g., Cole, Greenwood, and Sanchez 2016) or size-dependent policies, whereby Indian firms might be subject to steeper (implicit) tax rates (see, e.g., Hsieh and

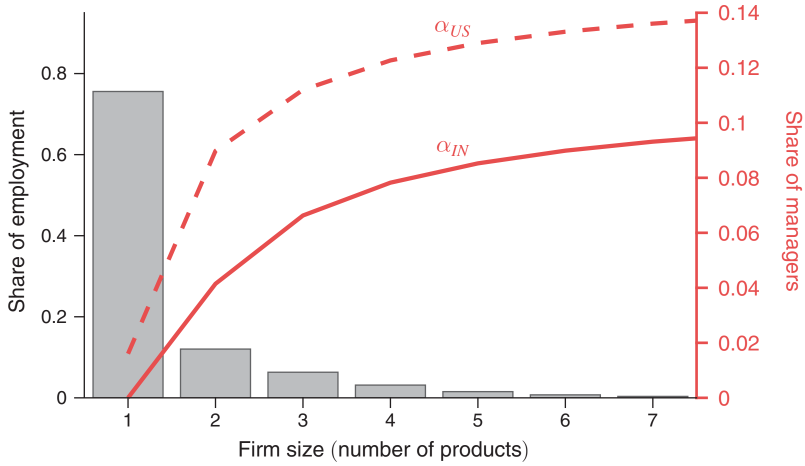


Figure 5. Identification of α

Note: This figure shows the share of managers by firm size for two values of α and the calibrated Indian firm size distribution.

Identifying the Management Elasticity σ.—We identify the parameter σ from the relationship between firm profits and managerial efficiency e. Using the profit function in (11) and the optimal amount of managerial efficiency $e = (\alpha\sigma/\omega_M)^{\frac{1}{1-\sigma}}$, profits can be written as

$$\tilde{\pi}(n) = (1-\sigma)e^{\sigma}n + \sigma T e^{-(1-\sigma)}. \tag{25}$$

Equation (25) highlights that σ governs the relationship between managerial services e and firm profits. In fact, if firms' managerial demand were homothetic, that is, if T were equal to zero, σ would exactly be the elasticity of profits with respect to e holding firm size n constant.

An ideal way to estimate σ is to exploit exogenous variation in managerial inputs at the firm level and subsequent changes in firm profitability. We, therefore, estimate σ via indirect inference and target the experimental evidence on the relationship between management practices and firm performance from Bloom et al. (2013).[17] The authors provided free consulting on the efficacy of 38 management practices to a set of randomly chosen textile establishments in India. These practices, which are standard in US firms, centered on factory operations, formalized quality control and inventory practices, and changes in human resource management, such as performance-based incentive pay. Using the random assignment of this managerial

Klenow 2014; Guner, Ventura, and Xu 2008; Ulyssea 2018; or Bento and Restuccia 2017). Similarly, inefficiencies in the allocation of start-up capital, bureaucratic red tape, or frictions in the labor market might induce more subsistence firms to enter in India ($\delta_{IND} < \delta_{US}$) or entry costs to be higher ($\theta^E_{IND} < \theta^E_{US}$).

[17] See also Bruhn, Karlan, and Schoar (2018) for a related management intervention for small and medium enterprises in Mexico.

intervention, Bloom et al. (2013) estimate the treatment effect of managerial practices on subsequent output growth using the specification

$$\ln Output_{i,t} = \beta \times TREAT_{i,t} + f_i + \epsilon_{i,t}, \tag{26}$$

where $TREAT_{i,t}$ takes the value of 1 for the treatment plants starting one month after the end of the intervention period, and f_i are a full set of plant fixed effects. They estimate (26) at the weekly level and find a treatment effect of 9 percent for a horizon of 100 weeks.

We use this treatment effect as an "identified moment" to identify σ (Nakamura and Steinsson 2018). To implement this experiment in our model, we need to take a stand on what the treatment means in our theory, that is, how we translate the ordinal nature of the treatment into a cardinal increase in managerial services e among treated firms. Our strategy is as follows. In our model, firms' managerial environment is fully summarized by their managerial services e. We, therefore, relate firm f's optimally chosen managerial services e_f to the share of practices that firm f chooses to adopt, which we denote by MP_f. Note that like e in our theory, the adoption decision of the managerial practices in the experiment was also endogenous. In particular, the experimental intervention provided management consulting but left the eventual choice of which practices to adopt to the firms. Bloom et al. (2013, p. 22) explicitly report that the adoption decision "was endogenous and it presumably varied with the cost-benefit calculation for each practice."

To link the unobservable e_f to the observable MP_f, we consider the measurement equation $e_f = \upsilon MP_f^{\varrho}$, where υ and ϱ are positive parameters. Letting MP_{IND}^{Treat} be the share of managerial practices adopted by Indian firms after the treatment and MP_{IND} be the share among control plants implies

$$\frac{e_{IND}^{Treat}}{e_{IND}} = \left(\frac{MP_{IND}^{Treat}}{MP_{IND}}\right)^{\varrho}.$$

For a given parameter ϱ, we can therefore infer the change in managerial service e due to the treatment from the change in managerial practices MP. To determine ϱ, we use data on differences in managerial practices between the United States and India and the model-implied differences in managerial services, e_{IND} and e_{US}. In particular, letting MP_{US} denote the share of practices adopted by US firms, our measurement equation implies $e_{IND}/e_{US} = (MP_{IND}/MP_{US})^{\varrho}$. Hence, we can map the observed change in managerial practices among treatment firms to the change in e as

$$\ln\left(\frac{e_{IND}^{Treat}}{e_{IND}}\right) = \varrho \times \ln\left(\frac{MP_{IND}^{Treat}}{MP_{IND}}\right) = \frac{\ln(e_{IND}/e_{US})}{\ln(MP_{IND}/MP_{US})} \times \ln\left(\frac{MP_{IND}^{Treat}}{MP_{IND}}\right). \tag{27}$$

In the microdata of the experiment, we find $MP_{IND} = 0.25$; that is, prior to the treatment, Indian firms adopt roughly one-fourth of the managerial practices. The treatment increases the adoption rate to $MP_{IND}^{Treat} = 0.63$. Given that all of these practices "have been standard for decades in the developed world" (Bloom et al. 2013, p. 43), we assume firms in the United States adopt all these practices; that is, $MP_{US} = 1$.[18] Furthermore, for a given calibration of our model, we can calculate e_{IND} and e_{US}. We can then use (27) to calculate e_{IND}^{Treat}.[19]

As we describe in detail in online Appendix Section B.2.1, our implementation takes the endogeneity of e_{IND}^{Treat} explicitly into account. In particular, we have to take a stand on *how* the experiment induced treatment firms to increase their e. Because the intervention provided information on how to use such managerial practices optimally, we model the treatment as a proportional increase in the productivity of treated firms' endogenous managerial services. Specifically, we assume treated firms' total managerial resources are given by ξe, and we choose ξ such that ξe^{Treat} coincides with the value implied by (27), where e^{Treat} denotes the optimal choice of e given ξ. In online Appendix Section B.2.1, we show ξ is given by $\xi = \left(e_{IND}^{Treat}/e_{IND}\right)^{1-\sigma}$. Importantly, we keep all general equilibrium variables constant in order to implement a partial equilibrium analysis consistent with the experiment.

We then relate this increase in managerial services to the resulting profits to estimate σ. Specifically, we take 50 firms from the very top of the firm size distribution of our calibrated Indian economy (consistent with the sample selection in Bloom et al. 2013), treat them with the management intervention as described above, simulate their evolution for 100 weeks, and then estimate the treatment effect according to (26) in the model-generated data. Whereas Bloom et al. (2013) estimate (26) using physical output as a measure of firm performance, we focus on total profits as the dependent variable in our model counterpart. We do so because profits are at the heart of our theory linking managerial services to firm performance.

Because the experiment was only conducted for firms in India, this strategy forces us to assume σ is common across countries.[20] Because of the importance of this parameter, we also implement a complementary identification strategy that does not rely on the experimental evidence, but only uses standard accounting data. The standard intuition from a constant elasticity production function suggests the output elasticity should be related to relative cost shares. The same intuition is true in our model: the higher σ, the larger the share of managerial compensation relative to profits. More specifically, our model implies

$$\frac{w_M nm(n)}{\Pi(n)} = \frac{\sigma}{1-\sigma}\left(1 - \frac{Tw_M}{\sigma\alpha\Pi(n)}\right), \tag{28}$$

where $w_M nm$ and $\Pi(n)$ denote total managerial payments and profits, respectively. Note that if firms had to rely only on outside managers, that is, if $T = 0$, the demand for outside managers would be homothetic and σ would reflect the relative compensation share. In our model, this mapping is slightly more complicated, but

[18] In online Appendix Section B.2.1, we use the reported management scores from Bloom and Van Reenen (2007) (which are available both for firms in the United States and for firms in India pre-treatment) to provide additional corroborating evidence for our assumption that $MP_{US} = 1$.

[19] To give a concrete example, our baseline calibration implies Indian firms utilize only 71 percent as many managerial services as firms in the United States; that is, $e_{IND}/e_{US} = 0.71$. Together with $MP_{US} = 1$, $MP_{IND} = 0.25$, and $MP_{IND}^{Treat} = 0.63$, (27) implies $e_{IND}^{Treat}/e_{IND} = 1.26$; that is, we infer the endogenous adoption of managerial practices from 0.25 to 0.63 corresponds to a 26 percent increase in managerial efficiency in treatment firms.

[20] Bloom, Sadun, and Van Reenen (2016) use managerial scores to estimate production functions for managerial inputs across countries. They find the coefficients on the managerial scores to be very similar across countries.

(28) shows the managerial compensation share is directly affected by σ. Because we can measure this moment both for the United States and India, this approach allows us to estimate σ separately for both countries. As we discuss in Section V, these approaches lead to similar results. In particular, the estimates for σ are almost identical between the United States and India and only slightly higher than the estimates implied by our indirect inference strategy.

Identifying the Remaining Management Parameters μ_M, ϑ, and T.—As we discuss in online Appendix Section B.2, all allocations in the model depend only on $\mu_M \times \alpha$. To separately identify the efficiency of managers within firms (α) from the supply of managerial skills (μ_M), we require variation in the demand for managerial skills, holding managerial human capital fixed. Intuitively, we would want to observe the same manager working with both the United States and the Indian α. We mimic this experiment by using data from the New Immigrant Survey (Jasso et al. 2014), which contains information about the pre- and post-migration occupations of recent immigrants to the United States and has recently been used by Hendricks and Schoellman (2018). In online Appendix Section B.2.2, we show in detail how we can use the managerial employment share of Indian migrants in India relative to their managerial employment share in the United States to identify μ_M and α separately. Intuitively, Indian immigrants to the United States are almost as likely to work in managerial occupations as US residents. However, they are much more likely to have worked in managerial jobs *prior* to emigrating. This finding implies that the average managerial human capital of the non-selected, non-migrant Indian population is lower than in the United States. These two moments separately identify α and μ_M and allow us to perform our counterfactual, where we change the delegation efficiency α while holding the supply of managerial skills μ_M constant.

To identify the dispersion of the managerial skill distribution, ϑ, we note that it can be directly calibrated to match the dispersion in managerial earnings. In particular, the model implies the variance of log managerial earnings to be given by ϑ^{-2}. Finally, the owner's time endowment T is a fixed factor, and firm profits are a renumeration for the provision of these services. We therefore calibrate T by targeting the entrepreneurial profit share, which is given by

$$\frac{\text{Aggregate Profits}}{\text{Total Sales}} = \frac{\sum_n \Pi(n) F_n}{Y} = \sum_n \tilde{\pi}(n) F_n, \tag{29}$$

where $F_n = F_n^H + \mathbf{1}(n = 1) F^L$ is the number of firms with n products and $\tilde{\pi}(n)$ is increasing in T, holding aggregate prices fixed (see (11)).

III. Estimation Results

In this section, we discuss our estimation results. Section IIIA contains the structural parameters and targeted moments. In Section IIIB, we show our model is also consistent with a variety of nontargeted moments. Finally, in Section IIIC, we use our estimated model to assess why firms in India are small.

Table 3—Estimated Parameters

Parameter	Interpretation	Target	US	India
Panel A. Internal calibration				
Firm dynamics				
θ	Expansion efficiency	Employment life cycle	0.196	0.058
δ	Share of high types	Exit profile by age (cond. on size)	0.602	0.111
β	Relative creative destruction	Employment share of old firms	4.659	2.852
θ_E	Entry efficiency	Entry rate	0.100	0.099
Managerial environment				
α	Delegation efficiency	Managerial employment share	0.433	0.206
μ_M	Average managerial human capital	Occupational sorting by immigrants	$1.000^{\dagger}$	0.405
ϑ	Dispersion of managerial human capital	Variance of ln managerial earnings	1.429	1.429^{*}
σ	Managerial output elasticity	Treatment effect of Bloom et al. (2013)	0.468^{*}	0.468
T	Entrepreneurial time endowment	Average entrepreneurial profit share	0.159	0.267
Panel B. External calibration				
ζ	Convexity of expansion costs		0.50	0.50
ρ	Discount rate		0.05	0.05

Notes: The table reports the parameter values that yield the model moments reported in Table 4. We denote normalized parameters by † and parameters that we do not estimate by *.

Table 4—Moments: Model versus Data

	US		India	
	Data	Model	Data	Model
Firm dynamics				
Entry rate (percent)	7.35	7.35	5.60	5.60
Exit profile by age (conditional on size)	1.59	1.59	1.11	1.09
Employment life cycle	2.55	2.55	1.11	1.12
Employment share of old firms (percent)	9.70	6.94	7.75	6.42
Managerial environment				
Managerial employment share (percent)	12.5	12.5	1.65	1.65
Treatment effect from Bloom et al. (2013) (percent)	N/A	N/A	9.00	9.00
Relative managerial share of Indian migrants	N/A	N/A	2.08	2.08
Average entrepreneurial profit share (percent)	21.0	21.0	48.3	46.2
Variance of ln manager earnings	0.49	0.49	0.45*	0.49

Notes: The table reports both the data moments and the corresponding moments in the model for the United States and India. We define *old* and *young* firms as firms of age 21–25 years and 0–5 years, respectively. We define small firms as firms with 1–4 employees in the data and with a single product in the model. The employment life cycle is the relative size of old firms relative to young firms. The conditional exit profile is the exit rate of young, small firms relative to old, small firms. See online Appendix Section B.1 for details. * denotes that the moment is not targeted in the calibration.

A. *Calibrated Parameters and Targeted Moments*

Tables 3 and 4 contain the calibrated parameters and the targeted moments. For convenience, Table 3 also reports the main target for the respective parameter even though the parameters are calibrated jointly. For the United States, we estimate seven parameters and for India, we estimate eight parameters.

Consider first Table 3. The top panel shows that 90 percent of entering firms in India are subsistence entrepreneurs. In contrast, entrants in the United States are about 6 times as likely to be high types ($\delta_{US} \approx 6 \times \delta_{IND}$) and such firms are around 3.5 times as efficient in expanding into new markets as their Indian counterparts ($\theta_{US} \approx 3.5 \times \theta_{IND}$). At the same time, the costs of creating such superior firms are almost the same between the United States and India ($\theta_{E,US} \approx \theta_{E,IND}$). Economically, we find these estimates plausible in that they capture the myriad reasons why firms in India might not expand (e.g., due to the presence of credit constraints or size-dependent policies) or why unproductive firms are abundant upon entry (e.g., because of low opportunity costs of entrepreneurship in India).

The next panel contains our estimates of the delegation environment. Our estimation implies delegation in the United States to be twice as efficient as in India ($\alpha_{US} \approx 2 \times \alpha_{IND}$). As highlighted above, this low estimate of α_{IND} is conditional on the other determinants of the firm size distribution, namely, θ, δ, and θ_E. In fact, if we only calibrated our model to the Indian firm-dynamic moments in panel A, but kept the delegation efficiency at the US level, the managerial employment share would be around 5 percent, that is, exceeding the level observed in India. Hence, although the fact that firms in India are small accounts for a sizable part of the lower share of managerial inputs, a less efficient delegation environment α is also required to explain the data.

We also estimate that managers in the United States have more human capital ($\mu_{M,US} > \mu_{M,IND}$). We infer this result from the fact that the share of managers among Indian immigrants in the United States is 12.7 percent (hence very similar to the overall manager share in the United States), but they are much *more* likely than the Indian population to work as managers prior to migrating. Therefore, the unselected population in India has a comparative disadvantage in managerial occupations.

In Table 4, we report the targeted moments. The first two columns contain the US calibration. Our model is able to rationalize most moments well. In particular, it matches the observed employment life cycle (whereby firms of age 21–25 years are about 2.5 times as large as firms younger than 5 years), the aggregate entry rate, and the differences in exit rates (whereby small young firms, which exit at a rate of 22 percent per year, are around 1.6 times as likely to exit as small old firms, which have an exit rate of 14 percent). The model slightly underestimates the aggregate employment share of old firms.[21]

The model also matches the aggregate share of managerial workers of 12.5 percent reported in Table 1, an entrepreneurial profit share of about 20 percent, and the dispersion of log managerial earnings.[22] Although we assume ϑ is identical across countries for simplicity, the dispersion of log managerial earnings in India is essentially the same as in the United States.[23]

The model is similarly successful in matching the moments of the Indian economy reported in columns 3 and 4. In particular, it replicates the essentially flat life cycle of Indian establishments, the low share of aggregate managerial employment,

[21] One reason 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 2018 or Garcia-Macia, Hsieh, and Klenow 2019), we could break this link.

[22] Empirically, we target the dispersion of residual log managerial earnings after controlling for industry fixed effects. To be able to compare India and the United States we use data for 2005 for the United States.

[23] Our distributional assumption of managerial human capital implies the average wage of managers relative to production workers within a country is given by $\vartheta/(\vartheta - 1)$. When we look at this implication in the microdata, we find that managers in the United States (India) earn a premium of 0.59 log points (0.67 log points). Both of these are lower than the model-implied premium given the estimate of ϑ, which is 1.19 log points. Because ϑ plays the role of a labor supply elasticity, we prefer to target the dispersion in wages, which is more directly related to the scope of selection. In Section V, we discuss how different assumptions about this supply elasticity affect our results.

and that young establishments exit almost at the same rate as old establishments. As is the case for the US calibration, the model slightly underestimates the share of old firms in the economy.[24] Also note firms in India have a much higher share of entrepreneurial profits than firms in the United States, because most firms in India are small, and the majority of their sales are attributed to entrepreneurial compensation for the provision of the fixed factor T.

Finally, our model is able to replicate the treatment effect of Bloom et al. (2013). This property is important, because to credibly quantify the aggregate effects of changes in the efficiency of delegation, it is reassuring that our model is quantitatively consistent with well-identified microeconomic evidence on the dynamic effects of changes in managerial efficiency at the firm-level. Matching the estimated treatment effect requires an estimate of σ around 0.47. As discussed in detail above, for our baseline analysis, we restrict σ to be the same across countries. In Section V, we discuss an alternative strategy where we estimate σ from accounting data and allow it to be country-specific.

B. *Nontargeted Moments*

Our model also performs well in matching a variety of nontargeted moments. In particular, we focus on the non-homotheticity of managerial demand, firms' survival hazards, and the number of products firms sell. Additionally, we also discuss some qualitative patterns in the delegation decisions of Indian firms based on a regression analysis and compare them with the predictions of our theory.

Non-Homothetic Managerial Demand.—A key mechanism of our model is that large firms endogenously increase their span of control by hiring outside managers. In particular, larger firms are more likely to hire any outside managers, and they hire more per product, conditional on hiring. Because the Indian data report managerial hiring at the firm level, we can look for these implications in the data.

Our model predicts both the extensive and intensive margin of managerial hiring well. Regarding the extensive margin, our model implies that firms that run their operations without outside managers account for 72 percent of aggregate employment in India. Empirically, we find this moment to be 77.5 percent in the Indian microdata. In Figure 6, we show that our model is also quantitatively consistent with the relationship between managerial employment shares and firm size conditional on hiring. To compare the model and the data (which we reported in Table 2), we focus on the quantiles of the firm size distribution. In particular, going from right to left, we plot the share of managerial employment among the largest 0.1 percent, the largest 1 percent, the largest 5 percent of firms, and so on. Hence, by going from right to left, we trace out the average managerial share as a function of the firm size distribution. At the far left, we report the share among the 100 percent largest firms, which is simply the entire sample of firms. Hence, in the data, the managerial

[24] At first glance, the fact that old firms have roughly the same aggregate employment share in the United States and India might be surprising. The reason is that the aggregate employment share of *very* old firms is much higher in the United States. In the United States (India), the share of firms older than 25 years is 55 percent (15 percent). See online Appendix Sections B.5 and B.6 for details.

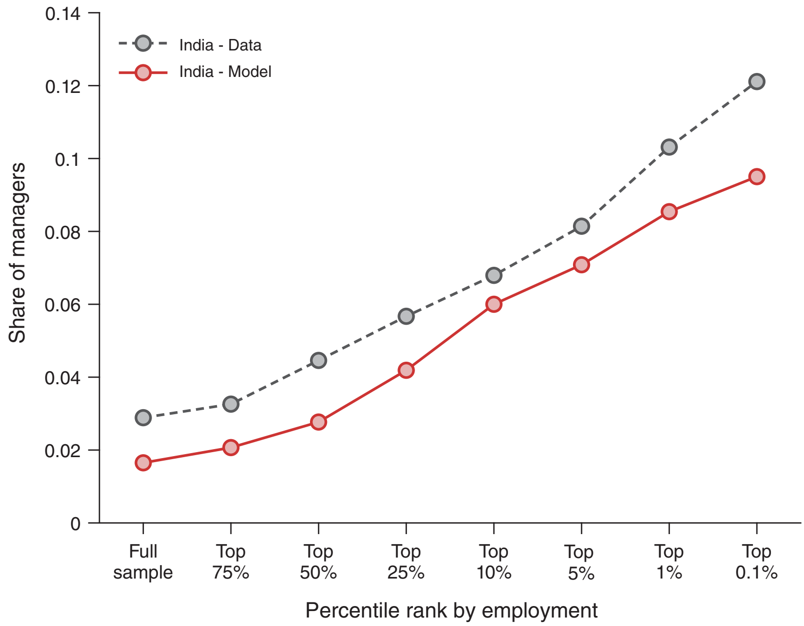


Figure 6. Managerial Demand by Firm Size

Notes: This figure shows the employment share of managers among firms in the top $x\%$ of the firm-size distribution for $x = 0.1\%, 1\%, 5\%, \ldots$. We report the data using a black dashed line and the model using a red solid line. See also Table 2 for a summary of the data.

share is the sample average of 2.9 percent (see Table 2), and in the model, it is 1.65 percent, our calibration target from the IPUMS data. Figure 6 shows that our model replicates the "delegation-firm size" relationship observed in India very well even though we do not target it explicitly.

Survival Hazards.—In Figure 7, we compare our model with two measures of the degree of selection. In panel A, we depict the survival rate, that is, the size of a given age cohort relative to the entering cohort. The rate of firm survival is reasonably similar in the United States and India, both in the data and in the model.[25] In panel B, we show the share of small firms by age (relative to their share among young firms). While the share of small firms in the United States declines to 40 percent by the age of 25, the vast majority of old firms in India are still small. Our model again replicates these patterns reasonably well.

The Distribution of Products.—In our model, a firm is a collection of product lines. Our calibration focuses only on employment data to measure firm size and does not use data at the product level. Both the US and the Indian data, however, contain information on the number of five-digit product codes in which individual

[25] As for the category of 26+ firms: note that the survival rate is the *accumulated* stock of surviving firms, that are older than 26 years. Hence, even though the US exit rates are only slightly lower than those in India, the small differences in the flow of exit add up to a sizable difference in the stock of old firms. See also Figures 2 and 3 in Hsieh and Klenow (2014), who show exit rates are only slightly lower in the United States but that the aggregate employment share of old firms is vastly larger in the United States.

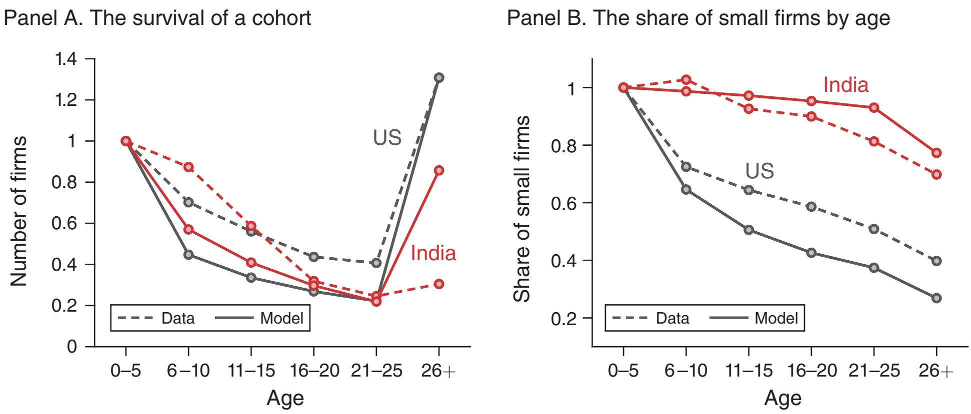


Figure 7. Firm Selection

Notes: Panel A depicts the share of firms by age relative to the share of firms in the youngest age category. Panel B shows the share of small firms by age. We show the data using solid lines and the model using dashed lines. In the United States, small firms are firms with one to four employees. In India, small firms are firms with one employee.

firms are operating.[26] In Figure 8, we plot the distribution of firm-level product counts in the data and the model. Our model matches this aspect of the data remarkably well, despite the fact that this moment is not targeted. In particular, the vast number of Indian firms indeed produce only a single product.

Qualitative Predictions on Delegation in the Indian Microdata.—Finally, we can look at some qualitative predictions of our theory.[27] Our theory implies firms do not hire outside managers if their size falls short of the delegation cutoff, that is, if $n < n^* = T(\omega_M/\sigma\alpha)^{\frac{1}{1-\sigma}}$. Hence, firms are more likely to delegate if (i) firm size n increases, (ii) the delegation efficiency α is larger, and (iii) the owner's inelastically provided managerial human capital T is smaller.

To take these predictions 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 entrepreneur's family as a proxy for T. Moreover, we use regional variation in trust within India to proxy for variation in α. The latter is calculated from the World Values Survey as the share of people providing the answer "Most people can be trusted" within the Indian state where the firm is located (Inglehart et al. 2014). This measure of trust is the one most commonly used in the literature (see, e.g., La Porta et al. 1997).

We then regress firms' managerial hiring decisions on firm size, household size, and regional trust in 22 Indian states. We always control for the market of a firm, that is, whether the firm is urban or rural, firm age, state-level GDP per capita, and

[26] The data for the US firms come from Acemoglu et al. (2018).

[27] See online Appendix Section B.4 for the details of the empirical analysis. There we also provide an explicit derivation of the regression equations based on our theory.

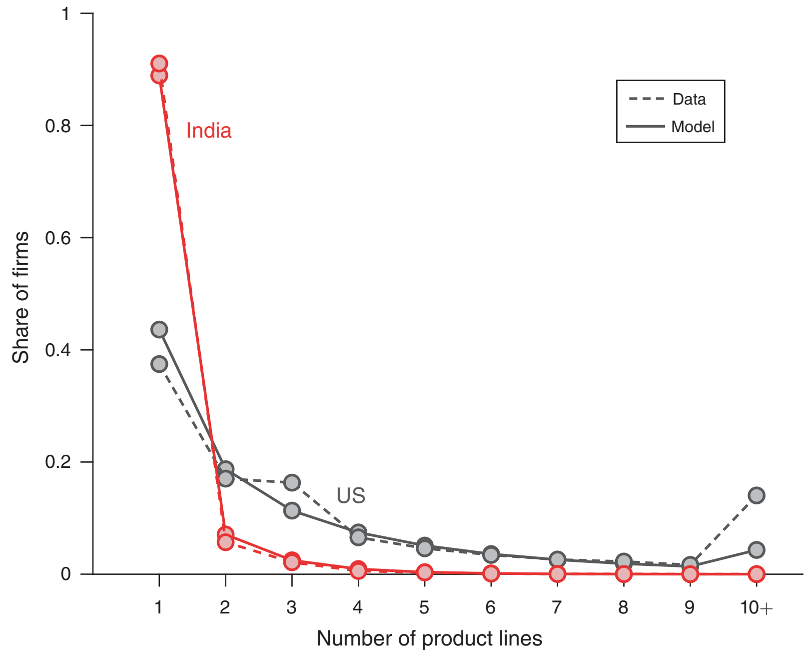


FIGURE 8. THE DISTRIBUTION OF PRODUCTS

Note: The figure shows the distribution of the number of products by firm in the data (dashed line) and the model (solid line).

two-digit sector fixed effects. Due to space constraints, we only report the estimated equation; the full analysis can be found in online Appendix Section B.4. We find that

$$\mathbf{1}(\textit{Firm hires managers}) = \underset{(0.003)^{***}}{0.039} \times \textit{Firm Size} - \underset{(0.001)^{**}}{0.003} \times \textit{Family Size}$$
$$+ \underset{(0.006)^{***}}{0.013} \times \textit{Trust},$$

where *Firm Size* and *Family Size* are the logarithms of the number of employees and household members, respectively. Hence, as predicted by our theory, firm size and regional trust correlate positively, whereas family size correlates negatively, with the probability of hiring an outside manager. These results are consistent with Bloom, Sadun, and Van Reenen (2012) who, using data from a survey on managerial practices, show firms in high-trust areas delegate more decision power to managers.

Our model also has implications for the relationship between family size and firm size. In our model, managerial resources within the family, T, are the constraining factor for firm size. This constraint, however, is less important the higher the delegation efficiency α. Hence, although 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. We can test this prediction from the interaction between trust and family size. This approach allows us to include a full set of state-fixed effects in the regression to control for all characteristics (including the level of trust) that are constant within Indian states. As before, we also control

TABLE 5—CREATIVE DESTRUCTION AND SELECTION

	India	US
Rate of creative destruction, τ	0.054	0.124
Share of high-type firms upon entry (δ)	0.111	0.602
Long-run share of high-type firms	0.344	0.946
Long-run employment share of high-type firms	0.470	0.983
Long-run share of high-type firms among firms of age 21–25	0.301	1.000

Notes: The table contains various equilibrium objects from the stationary distribution of the calibrated models. The models are parametrized according to Table 3.

for the location of the firm (rural versus urban), firm age, and two-digit sector fixed effects. We find that

$$\textit{Firm Size} = \underset{(0.278)^{***}}{0.812} \times \textit{Family Size} - \underset{(0.758)^{*}}{1.329} \times \textit{Family Size} \times \textit{Trust}.$$

Hence, the correlation between family size and firm size is positive and particularly strong in low-trust regions. Through the lens of our model, this pattern is due to the imperfections in delegation in those regions.

C. *Why Are Indian Firms Small? The Role of Selection and Creative Destruction*

The estimated model allows us to give a structural interpretation of the observed differences in firm dynamics between the United States and India. Our theory stresses that two key determinants are the extent of selection and the rate of creative destruction. Although neither of these mechanisms is directly observable, we can measure them through the lens of the model.

In Table 5, we report a set of statistics from the stationary distribution. First, note our calibration implies that creative destruction in the United States is twice as large as in India. At first glance, it seems surprising that we infer large differences in creative destruction despite the fact that both aggregate entry and exit rates and firms' survival probabilities by age are quite similar (see Figure 7). The key to reconciling these facts is to realize that the underlying distributions of firm size are vastly different between the United States and India. 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. The fact that exit rates are quite similar despite the fact that many firms in India are small and hence close to the exit threshold implies creative destruction in India has to be substantially smaller. Conversely, most creative destruction in the United States takes place in infra-marginal markets where firms lose market share without exiting.

In the remaining rows of Table 5, we report different aspects of the degree of selection. In the stationary distribution of the United States, around 95 percent of firms are high-type firms (compared to 60 percent at the time of entry), and they have a combined employment share of 98 percent, because they are bigger on average. In India, even in the long-run, high-type firms account for only 34 percent of firms and 47 percent of aggregate employment. This slower weeding-out process of low-type firms in India is also highlighted by the fact that even among old firms, more than

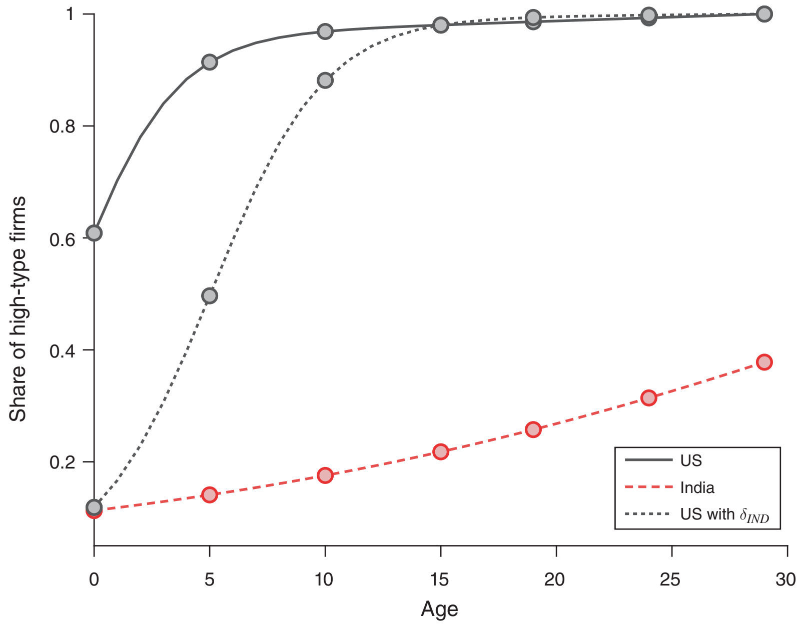


Figure 9. Endogenous Selection

Notes: The figure shows the share of high-type firms by age both for the India calibration (red line) and for the US calibration (black line). It also shows the counterfactual share of high-type firms by age if the initial share of high-type firms in a cohort in the United States is given by its Indian counterpart δ_{IND}. All calibrated parameters are taken from Table 3.

two-thirds of them are subsistence entrepreneurs. This finding is in stark contrast to the United States, where the population of old firms consists only of high types.

In Figure 9, we display the dynamics of this "shake-out" process by tracing out the share of high-type firms within a cohort at different ages. Not only is the share of high-type firms in the United States significantly greater among the entering cohort, they also grow much faster, creating a much stronger selection force. This selection process is dampened in India: even among 30-year-old plants, more than one-half are low-type firms. Importantly, this lack of selection in India is not only due to fact that few high-type firms exist to begin with. To illustrate this distinction, we simulate a counterfactual cohort of US firms that starts with the initial type distribution of India, that is, where the initial share of high-type firms is δ_{IND}. Figure 9 shows that differences in growth incentives of high-type firms in the United States and India are a key aspect of the selection dynamics: by the age of 15, this counterfactual cohort in the United States would again be populated by mostly high-type firms.

IV. The Aggregate Importance of Delegation Efficiency

To what extent are differences in the efficiency of delegation responsible for the observed differences in firm dynamics and aggregate economic performance between the United States and India? To answer these questions, we study a counterfactual Indian economy where we increase α from α_{IND} to α_{US} while keeping the rest of the parameters at their calibrated levels. We first quantify the effects on firm-level

Table 6—Increasing the Delegation Efficiency in India: Firm-Level Implications

	Average	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
Panel A. Equilibrium outcomes						
Expansion rate $x(n;\alpha)$ (percent)	+23.69	+14.36	+18.97	+20.73	+21.49	+21.87
Entry intensity $z(\alpha)$ (percent)			+1.44			
Creative destruction τ (percent)			+4.11			
Share of outside managers (percent)			+138			
Panel B. Implications for firm dynamics						
Average firm size (percent)			+3.59			
Share of high-type firms (percent)			+3.21			
Employment share of small firms (percent)			−3.00			
	Effects by age					
	≤5	6–10	11–15	16–20	21–25	+26
Average firm size (percent)	2.17	2.20	2.31	2.54	2.89	4.98
Share of small firms (percent)	−0.08	−0.29	−0.58	−0.97	−1.51	−5.00

Notes: The table reports the changes in various equilibrium outcomes after increasing the delegation efficiency in India from α_{IND} to α_{US}. Small firms are those with a single product. All changes refer to changes in the stationary distribution.

outcomes. We then turn to the aggregate effects and study the link between α and aggregate income differences.

A. *Delegation Efficiency and Firm Dynamics*

The firm-level implications are summarized in Table 6. In panel A, we focus on the changes in firm expansion, entry, and creative destruction. Incumbents' expansion incentives are much more responsive than the entry margin. While firms' expansion rates increase by 24 percent, on average, the entry intensity increases only by 1.4 percent. These differences arise because outside managers are complementary to firm size and therefore are not very important for subsistence firms, which never grow. This complementarity also implies the expansion rate of large firms is particularly responsive.

At the aggregate level, however, the increase in creative destruction is much closer to the change in the entry intensity. The reason is that the market share of high-type firms in India is relatively small, so the majority of creative destruction is accounted for by new entrants. Finally, the equilibrium employment share of outside managers would more than double to 3.9 percent. Note this is still well below the level in the United States, because Indian firms are still substantially smaller than their US counterparts.

In panel B, we report the implications for the resulting process of firm-dynamics. If Indian firms could employ outside managers as efficiently as firms in the United States, average firm size would increase by 3.6 percent, the share of high-type firms would increase by 3.2 percent, and the importance of small producers would decline by 3.0 percent.[28] The last two rows of panel B show these changes stem mostly

[28] Our calibrated model predicts that firms in the United States are, on average, roughly 2.5 times as large as firms in India. This number is not comparable to the empirical size difference of 15.8 as reported in Table 1. The reason is that in our model, entrants in the United States start at the same size as entrants in India. Empirically,

Table 7—Decreasing Delegation Efficiency in the United States

Panel A. Equilibrium outcomes (*percent*)			*Panel B. Implications for firm dynamics* (*percent*)			
Average expansion rate	Entry intensity	Creative destruction	Average firm size	Share of high type firms	Employment share small firms	Share of managers
−28.7	−10.0	−24.9	−13.6	−0.3	+19.1	−57.0

Notes: The table reports the changes in various equilibrium outcomes after decreasing the efficiency of delegation in the United States from α_{US} to α_{IND}. *Small firms* are those with a single product. All changes refer to changes in the stationary distribution.

from older firms, which are, on average, larger and hence more likely to rely on outside managers. Quantitatively, firms between 21 and 25 years old experience an employment increase by 2.9 percent and their share of single-product firms decline by 1.5 percent. The reason why these effects are small compared to the increase in high types' expansion rate, $x(n;\alpha)$, is again due to the lack of selection because even among old firms, the majority of firms in India are subsistence producers. The effect of α on the process of firm dynamics in India is therefore modest.

The Importance of Complementarities.—The results in Table 6 highlight the interaction between the ease of delegation and other aspects of the economy. In particular, improvements in the efficiency of delegation are more potent if high-type firms are plentiful and those firms can expand easily. To see that this intuition is indeed correct, Table 7 presents the US analogue of Table 6.[29] Compared to the results for the Indian economy, we find that a decrease in the efficiency of delegation in the United States to the Indian level would affect firm growth substantially. In particular, the rate of creative destruction decreases by 25 percent, average firm size declines by 14 percent, and the employment share of small firms increases by 19 percent. Similarly, the effects on managerial hiring are also larger in the United States. If outside managers were as inefficient as their Indian counterparts, the equilibrium managerial share would decline from 12.5 percent to 5.4 percent. The reason for such stark differences is that high-type firms are abundant in the United States and their expansion costs are low. Preventing these dynamic entrepreneurs from growing affects the process of firm dynamics substantially.

B. *Delegation Efficiency and Aggregate Income Differences*

How important are frictions to delegating decision power in Indian firms for the gap in income per capita gap between India and the United States? To answer this question, we need to specify the evolution of the step size γ_t. Because we can estimate all other parameters of the model independently, our earlier results do not depend on these assumptions in any way.

entrants in the United States have, on average, 13.7 employees, whereas entrants in India have 2.5. Entrants in the United States are therefore 5.5 times as large as entrants in India. Hence, relative to the initial size difference, US firms are $15.8/5.5 = 2.8$ times as large as firms in India.

[29] For brevity, we only report the aggregate outcomes. The results by firm size and firm age are available upon request.

We consider a parametrization of our model where the distribution of income between the United States and India is stationary in the long run. More specifically, we assume the Indian economy (by being technologically backward relative to the United States) benefits from "catch-up" growth and a higher step-size γ. To capture this intuition in a parsimonious way, we assume the Indian step-size $\gamma_{IND,t}$ is related to the technological gap $Q_{US,t}/Q_{IND,t}$ and given by

$$\gamma_{IND,t} = \gamma_{US} \times \left(\frac{Q_{US,t}}{Q_{IND,t}}\right)^{\lambda}, \tag{30}$$

where $\lambda \geq 0$ and γ_{US} is the step size for the United States, which we assume is constant.[30] Equation (30) captures, in a reduced-form way, the presence of knowledge spillovers. If $\lambda > 0$, the lower the relative technology in India, the higher the innovation step size. If $\lambda = 0$, no advantages from backwardness exist.

Importantly, the formulation in (30) implies income differences between the United States and India will be constant in the long-run. Along a BGP where $g = \ln(\gamma_{US})\tau_{US} = \ln(\gamma_{IND})\tau_{IND}$, equation (30) yields

$$\ln\left(\frac{Q_{IND,t}}{Q_{US,t}}\right) = \frac{\ln\gamma_{US} - \ln\gamma_{IND}}{\lambda} = \frac{\ln\gamma^{US}}{\lambda} \times \left(\frac{\tau_{IND} - \tau_{US}}{\tau_{IND}}\right). \tag{31}$$

This expression highlights that the long-run distribution of technology Q across countries is stationary and determined by differences in creative destruction. Differences in delegation efficiency α, by affecting the rate of creative destruction, therefore manifest themselves in level differences, not in growth differences in the long run. During the transition, an increase in α increases the growth rate of $Q_{IND,t}$. In addition, a change in α has static consequences because it increases the amount of managerial efficiency units, $\mathcal{M}_t$, and hence increases income per capita, holding the level of Q_t fixed (see (6)).

To quantify the strength of these forces, we consider an experiment where in 2010 the delegation efficiency in India increases unexpectedly and permanently from α_{IND} to α_{US}. We then trace out the dynamic evolution of the Indian economy. To do so, we need to calibrate γ_{US}, λ, and the initial productivity differences between the United States and India. We assume the US economy is on a BGP, and choose γ^{US} to match a growth rate of 2 percent, given the rate of creative destruction reported in Table 5. India, in contrast, is still catching up to the US economy. Empirically, relative productivity in the United States, vis-à-vis India, decreased substantially from about 4 in 1985 to 3.2 in 2005 (see online Appendix Section B.2, in particular Figure 2). We therefore calibrate λ and the relative productivity between the United States and India in 1985, $Q_{IND,1985}/Q_{US,1985}$, to match these time-series dynamics. This exercise implies $\lambda = 0.296$.[31]

[30] Taking the United States as the frontier economy is purely for simplicity. Suppose there is an exogenous technological frontier $Q_{F,t}$, which grows at rate g. Suppose the step size in country c is given by (30) *relative* to this frontier, that is, $\gamma_{c,t} = \gamma \times (Q_{F,t}/Q_{c,t})^{\lambda}$. If the US economy has already reached its BGP, (30) holds with $\gamma_{US} = g/\tau_{US}$.

[31] Whereas we use plant-level data from the manufacturing sector for the firm-related moments, here we rely on data about aggregate TFP. As long as relative TFP in the manufacturing sector, $TFP_{IND}^{Manu}/TFP_{US}^{Manu}$, shows the same rate of catch-up, our analysis will be valid. If aggregate TFP in India were to show faster catch-up (e.g., due to the

In Table 8, we summarize the aggregate implications of this experiment. In panel A, we report the implications for the growth rate of the technology index Q_t. On impact, the growth rate increases by about 0.16 percentage points in 2010. Over time, this growth rate differential between the baseline and the counterfactual Indian economy declines, and in the long run, both countries grow at the same rate. In panel B, we calculate the cumulative effect of this higher growth rate on the (relative) level of Q_t. In 2000, the technology in India is about 26.6 percent of the US level. Our baseline estimates imply that long-run technological differences between the United States and India would be 49.5 percent. If delegation in India were as seamless as in the United States, relative technology in India would be equal to 52 percent. Hence, limits to delegation can account for $(51.9 - 49.3)/(100 - 49.3) \approx 5.0$ percent of the long-run technological gap between the United States and India.

The effects on income per capita, shown in panel C, are larger. In the long run, an increase in the efficiency of delegating managerial tasks would increase relative income per capita in India from 51.7 percent to around 57.0 percent. This increase accounts for $(57.0 - 51.7)/(100 - 51.7) \approx 11$ percent of the aggregate gap in income per capita. The effects are larger because of the static effects captured by $\mathcal{M}$. In particular, the magnitudes of the static effects of better delegation and the dynamic effects operating through higher creative destruction are roughly equal.[32] For completeness, we also report the long-run change in consumption per capita in panel D, which, in contrast to the comparison of income per capita, also takes the resources spent on entry and expansion efforts into account.

V. Robustness

In this section, we discuss the robustness of our results. For each specification, we recalibrate both the US and the Indian economy and redo our analysis. Overall, we find our main conclusions are fairly robust. All results are reported in Table 9. We report the implied levels of creative destruction in both countries (columns 1 and 2) as a summary statistic of the respective calibrations and the changes in creative destruction, relative technology and income, average firm size, and the share of small firms among 21- to 25-year-old firms in India due to an increase in α to the US level. In panel A of Table 9, we report our baseline results for comparison.

To summarize: our baseline calibration is qualitatively robust across the different alternatives we consider. The most important parameters are the "management elasticity" σ, the elasticity of labor supply, and the dispersion of managerial human capital ϑ.

Alternative Estimates of σ.—Our baseline estimates of σ are identified from the estimated treatment effect of the managerial intervention of Bloom et al. (2013). A concern with this strategy is that we had to restrict σ to be constant across

reallocation of workers out of agriculture), our estimate of λ would be upward biased and we would underestimate the aggregate consequences of changes in α: see equation (31).

[32] Additionally, the increase in α also reduces the number of production workers as individuals sort into managerial occupations. Quantitatively, the number of production workers declines by about 2.3 percent along the BGP.

Table 8—Increasing Delegation Efficiency in India: Macroeconomic Implications

Year	2000	2010	2020	2030		∞
Panel A. Productivity growth g_Q (percent)						
Baseline	3.00	2.85	2.72	2.62	…	2.00
$\alpha = \alpha_{US}$	3.00	3.01	2.84	2.71	…	2.00
Panel B. Relative productivity Q_{IND}/Q_{US} (percent)						
Baseline	26.6	29.2	31.6	33.8	…	49.5
$\alpha = \alpha_{US}$	26.6	29.2	32.0	34.6	…	52.0
Panel C. Relative income per capita y_{IND}/y_{US} (percent)						
Baseline	27.8	30.5	33.0	35.3	…	51.7
$\alpha = \alpha_{US}$	27.8	32.6	35.5	38.3	…	57.0
Panel D. Relative consumption c_{IND}/c_{US} (percent)						
Baseline	29.1	31.9	34.6	36.9	…	54.1
$\alpha = \alpha_{US}$	29.1	33.9	37.0	39.9	…	59.5

Notes: The table reports the aggregate implications of an increase in the efficiency of delegation in India from α_{IND} to α_{US} in the year 2010. We report the rate of growth of the productivity index Q_t (panel A), the differences in Q_t between the United States and India (panel B), the differences in income per capita (panel C), and the differences in consumption per capita (panel D). These results are based on an estimate for λ of 0.296 (see online Appendix Section B.2).

countries. In panels B and C, we report the results from an alternative strategy that addresses these limitations. In panel B, we consider a calibration, which does not rely on the experimental results of Bloom et al. (2013), but instead uses the share of managerial compensation in total profits to identify σ (see (28)).[33] Because we observe this moment in both countries, this strategy allows us to let σ vary across countries. Our calibrated model is able to match this moment in both countries. We estimate that $\sigma_{IND} = 0.51$ and $\sigma_{US} = 0.67$, which are higher than our baseline estimate of $\sigma = 0.47$. In panel C, we use both the estimated treatment effect and the managerial compensation shares as moments, and we find $\sigma_{IND} = 0.46$ and $\sigma_{US} = 0.67$. These estimates for σ amplify the aggregate consequences of an increase in α.

Entry.—In our benchmark specification, we assume entrants have access to the same innovation technology as incumbent firms; that is, the cost function has an elasticity governed by $\zeta_e = \zeta = 0.5$. To assess the importance of this parameter, we recalibrate our model, both for the United States and India, while setting ζ_e to alternative values. The higher the value of ζ_e, the more responsive are entrants to changes in the value of entry. As shown in panel D, if we set ζ_e to 0.4 (0.6), the effects of improving the efficiency of outside managers are smaller (larger). In terms of income per capita, our baseline results decrease (increase) by 0.5 percentage points. As expected, a higher entry elasticity reduces the effect on average firm size.

Convexity of Incumbents' Expansion Technology.—Similarly, we studied how the convexity of the expansion cost function for incumbent firms changes our results. Interestingly, the results are the opposite of the ones found in panel D: the higher

[33] In online Appendix Section B.1, we discuss in detail how we measure this moment.

Table 9—Robustness

	τ_{IND}	τ_{US}	Percent change in … due to the increase from α_{IND} to α_{US}: τ_{IND}	Q_{IND}/Q_{US}	y_{IND}/y_{US}	Average firm size	Share of small firms
Panel A. Baseline calibration							
	0.054	0.124	4.11	5.05	10.25	3.59	−1.51
Panel B. Estimating country-specific σ from accounting information							
	0.057	0.129	4.83	6.88	13.94	0.63	−1.00
Panel C. Estimating country-specific σ from Bloom et al. (2013) and accounting information							
	0.056	0.111	5.31	8.11	15.25	2.30	−1.45
Panel D. Entry elasticity ζ_e							
$\zeta_e^L = 0.4$	0.054	0.124	3.77	4.63	9.76	3.70	−1.49
$\zeta_e^H = 0.6$	0.054	0.124	4.55	5.58	10.88	3.44	−1.53
Panel E. Convexity of expansion technology ζ							
$\zeta^L = 0.4$	0.054	0.122	4.19	5.19	10.94	2.15	−1.08
$\zeta^H = 0.6$	0.054	0.127	3.90	4.70	9.25	5.04	−2.05
Panel F. Estimation with firm-level data							
	0.054	0.116	4.12	5.12	10.47	2.90	−1.43
Panel G. Strength of knowledge diffusion λ							
$\lambda^L = 0.217$	0.054	0.124	4.11	6.95	12.24	3.59	−1.51
$\lambda^H = 0.423$	0.054	0.124	4.11	3.51	8.63	3.59	−1.51
Panel H. Elastic labor supply in the manufacturing sector							
$\Delta L/L = 2$ percent	0.054	0.124	5.62	6.87	14.62	3.78	−1.79
$\Delta L/L = 5$ percent	0.054	0.124	7.88	9.54	21.29	4.08	−2.22
Panel I. Dispersion in managerial human capital ϑ							
	0.052	0.120	1.56	2.13	3.32	6.45	−0.70

Notes: Panel A contains our baseline results based on the parameters reported in Table 3. In panels B and C, we estimate σ based on accounting information and allow it to differ across countries. In panel D, we consider two different values for the elasticity of the entry technology, $\zeta_e^L = 0.4$ and $\zeta_e^H = 0.6$. In panel E, we consider two different values for the convexity of the innovation function, $\zeta^L = 0.4$ and $\zeta^H = 0.6$. In panel F, we report the results when we calibrate the model for the US economy to firm-level moments. In Panel G, we consider two values for λ, which controls the strength of the knowledge diffusion in step size for India, $\lambda^L = 0.217$ and $\lambda^H = 0.423$. These values are chosen such that the speed of convergence (in terms of half-life) is 25 percent longer (λ^L) and 25 percent shorter (λ^H) compared to the baseline Indian economy. In panel H, we allow the total workforce to increase by 2 or 5 in response to the change in α. In panel I, we consider a value for ϑ of 2.24.

(lower) the elasticity of incumbent innovation, the weaker (stronger) the response of aggregate income and creative destruction to changes in α. The reason is that, in India, entrants account for most creative destruction. The higher the incumbent expansion elasticity, the more entrants are crowded out. Although such a higher elasticity increases average firm size, it actually reduces the aggregate impact of changes in α.

Firm-Level Analysis.—For our baseline analysis, we have focused solely on establishment-level data. We did so to ensure comparability between the United States and India, because we cannot link individual establishments to specific firms in the Indian data. Panel F shows this choice has no substantial implications for our conclusions: the counterfactual implications of an increase in α are quantitatively similar when we calibrate the US parameters to firm-level moments.[34]

Strength of Knowledge Diffusion.—Our benchmark analysis estimates the diffusion parameter λ from the time series of TFP differences between India and the United States. Our estimate implies a half-life of around 50 years. We considered two alternative values for λ that increase (reduce) the speed of convergence by 25 percent. This parameter only affects aggregate income differences and not the firm size distribution. Panel G of Table 9 shows that a faster transition speed (i.e., a high level of λ) decreases the impact of α on productivity and income differences. This follows directly from (31), which shows that Q_{IND}/Q_{US} is less sensitive to changes in τ if λ is large. The quantitative results are, however, in the ballpark of our baseline estimates.

Elastic Labor Supply.—In our main analysis, we treated aggregate labor supply as exogenous and hence non-responsive to an increase in α. If an increase in delegation efficiency in the manufacturing sector raises productivity, we might expect the manufacturing sector to draw in workers from the rest of the economy. In panel H, we report the results when we assume the total workforce in the manufacturing sector increases by 2 percent or 5 percent when α is increased to the US level. Allowing for elastic labor supply amplifies our results because an increase in the workforce increases creative destruction and hence reduces income differences.

Dispersion in Managerial Human Capital ϑ.—For our baseline estimates, we use the dispersion in log managerial earnings to calibrate the dispersion in managerial human capital ϑ. Our assumption regarding the managerial skill distribution implies that average managerial earnings relative to those of production workers are given by $\vartheta/(\vartheta - 1)$ (see also footnote 23). The managerial earnings premium of 0.59 log points in the United States implies a higher ϑ value of 2.24. Panel I shows the results based on this higher value. This parameter is quite important in that the change in relative income per capita due to the increase in α declines from 10 percent to 3.3 percent. The main reason is that a higher ϑ makes the labor supply of managers more elastic. A given change in α therefore induces a sharper decline in the number of workers, which in turn tends to lower profits and hence weakens the effect on expansion, entry, and creative destruction.

VI. Conclusion

Are inefficiencies in delegating managerial tasks to outside managers an important determinant of the process of firm dynamics and aggregate income in poor

[34] The model is able to match the firm-level moments quite well. The main difference between establishments 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 establishments), and the relative exit rate of young firms is higher than that of older establishments, because old firms exit less frequently than older establishments. Moreover, the aggregate entry rate is slightly lower at the firm level. In online Appendix Section B.5, we provide more details on the establishment-firm comparison for the United States.

countries? To answer this question, we proposed a novel model of firm growth that highlights the interaction between managerial delegation, firms' incentives to expand, and aggregate productivity. Our theory predicts an inherent complementarity between the efficiency of delegation and firm size, because delegation only becomes necessary once firms reach a certain scale. If firms anticipate they will not be able to delegate efficiently once they grow large, their incentives to expand are throttled. At the micro level, this implies most firms stay small. At the macro level, it reduces the extent of reallocation, allows stagnant, subsistence producers to survive, and lowers aggregate productivity.

To quantify the strength of this mechanism, we calibrate our model to plant-level data from India and the United States. To credibly identify the link between managerial inputs and firms' incentives to expand, we estimate our structural model to the experimental evidence on the relationship between management practices and firm performance reported in Bloom et al. (2013).

We draw three lessons from our quantitative analysis. First, we find that the Indian economy suffers from a lack of selection, which allows subsistence firms to survive. The glut of small firms in poor countries may therefore not result from frictions these firms face, but rather may be a sign that other, more dynamic firms do not grow sufficiently. Policies targeted at small firms could therefore end up supporting stagnant producers and have unintended consequences.

Second, we find that inefficiencies in delegating managerial tasks have nontrivial macroeconomic implications. Our estimates imply that a given manager is only one-half as efficient in an Indian firm, relative to a firm in the United States. If Indian firms could use managers as efficiently as US firms, income per capita difference between these two countries would be 11 percent lower. This increase is due to both static and dynamic effects that are of roughly equal size.

Finally, we find a strong complementarity between delegation efficiency and other factors affecting firm growth. Whereas an increase to US standards would increase average firm size in India only modestly, firms in the United States would shrink substantially if they had to operate with the delegation environment common in India. Hence, for improvements in the efficiency of delegation to have sizable effects in India, other determinants of firm growth also need to be addressed: even if one of its wheels is fixed, a car cannot run when the rest of its wheels remain broken.

REFERENCES

Acemoglu, Daron, Ufuk Akcigit, Harun Alp, Nicholas Bloom, and William Kerr. 2018. "Innovation, Reallocation, and Growth." *American Economic Review* 108 (11): 3450–91.

Aghion, Philippe, Ufuk Akcigit, and Peter Howitt. 2014. "What Do We Learn from Schumpeterian Growth Theory?" In *Handbook of Economic Growth*, Vol. 2, edited by Philippe Aghion and Steven N. Durlauf, 515–63. Amsterdam: Elsevier.

Aghion, Philippe, and Peter Howitt. 1992. "A Model of Growth through Creative Destruction." *Econometrica* 60 (2): 323–51.

Akcigit, Ufuk. 2017. "Economic Growth: The Past, the Present, and the Future." *Journal of Political Economy* 125 (6): 1736–47.

Akcigit, Ufuk, Harun Alp, and Michael Peters. 2021. "Replication Data for: Lack of Selection and Limits to Delegation: Firm Dynamics in Developing Countries." American Economic Association [publisher], Inter-university Consortium for Political and Social Research [distributor]. https://doi.org/10.3886/E119504V1.

Akcigit, Ufuk, and William R. Kerr. 2018. "Growth through Heterogeneous Innovations." *Journal of Political Economy* 126 (4): 1374–443.

Asker, John, Allan Collard-Wexler, and Jan De Loecker. 2014. "Dynamic Inputs and Resource (Mis) Allocation." *Journal of Political Economy* 122 (5): 1013–63.

Banerjee, Abhijit V., Emily Breza, Esther Duflo, and Cynthia Kinnan. 2015. "Do Credit Constraints Limit Entrepreneurship? Heterogeneity in the Returns to Microfinance." Unpublished.

Bennedsen, Morten, Kasper Meisner Nielsen, Francisco Pérez-Gonzalez, and Daniel Wolfenzon. 2007. "Inside the Family Firm: The Role of Families in Succession Decisions and Performance." *Quarterly Journal of Economics* 122 (2): 647–91.

Bento, Pedro, and Diego Restuccia. 2017. "Misallocation, Establishment Size, and Productivity." *American Economic Journal: Macroeconomics* 9 (3): 267–303.

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

Bloom, Nicholas, Benn Eifert, Aprajit Mahajan, David McKenzie, and John Roberts. 2013. "Does Management Matter? Evidence from India." *Quarterly Journal of Economics* 128 (1): 1–51.

Bloom, Nick, Raffaella Sadun, and John Van Reenen. 2009. "Americans Do I.T. Better: US Multinationals and the Productivity Miracle." Unpublished.

Bloom, Nicholas, Raffaella Sadun, and John Van Reenen. 2012. "The Organization of Firms across Countries." *Quarterly Journal of Economics* 127 (4): 1663–705.

Bloom, Nicholas, Raffaella Sadun, and John Van Reenen. 2016. "Management as a Technology?" NBER Working Paper 22327.

Bloom, Nicholas, and John Van Reenen. 2007. "Measuring and Explaining Management Practices across Firms and Countries." *Quarterly Journal of Economics* 122 (4): 1351–408.

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

Brooks, Wyatt, and Kevin Donovan. 2017. "Eliminating Uncertainty in Market Access: Evidence from New Bridges in Rural Nicaragua." Unpublished.

Bruhn, Miriam, Dean Karlan, and Antoinette Schoar. 2018. "The Impact of Consulting Services on Small and Medium Enterprises: Evidence from a Randomized Trial in Mexico." *Journal of Political Economy* 126 (2): 635–87.

Buera, Francisco J., Joseph P. Kaboski, and Yongseok Shin. 2011. "Finance and Development: A Tale of Two Sectors." *American Economic Review* 101 (5): 1964–2002.

Caselli, Francesco, and Nicola Gennaioli. 2013. "Dynastic Management." *Economic Inquiry* 51 (1): 971–96.

Chandler, Alfred Dupont. 1990. *Strategy and Structure: Chapters in the History of the Industrial Enterprise*. Cambridge, MA: MIT Press.

Cole, Harold L., Jeremy Greenwood, and Juan M. Sanchez. 2016. "Why Doesn't Technology Flow from Rich to Poor Countries?" *Econometrica* 84 (4): 1477–521.

Decker, Ryan, John Haltiwanger, Ron Jarmin, and Javier Miranda. 2014. "The Role of Entrepreneurship in US Job Creation and Economic Dynamism." *Journal of Economic Perspectives* 28 (3): 3–24.

de Mel, Suresh, David McKenzie, and Christopher Woodruff. 2008. "Returns to Capital in Microenterprises: Evidence from a Field Experiment." *Quarterly Journal of Economics* 123 (4): 1329–72.

Flood, S., M. King, R. Rodgers, S. Ruggles, and J. R. Warren. 2020. "Integrated Public Use Microdata Series, Current Population Survey: Version 7.0 [dataset]." Minneapolis, MN: IPUMS. https://doi.org/10.18128/D030.V7.0.

Garcia-Macia, Daniel, Chang-Tai Hsieh, and Peter J. Klenow. 2019. "How Destructive Is Innovation?" *Econometrica* 87 (5): 1507–41.

Garicano, Luis, Claire Lelarge, and John Van Reenen. 2016. "Firm Size Distortions and the Productivity Distribution: Evidence from France." *American Economic Review* 106 (11): 3439–79.

Garicano, Luis, and Esteban Rossi-Hansberg. 2015. "Knowledge-Based Hierarchies: Using Organizations to Understand the Economy." *Annual Review of Economics* 7: 1–30.

Gourio, François, and Nicolas Roys. 2014. "Size-Dependent Regulations, Firm Size Distribution, and Reallocation." *Quantitative Economics* 5 (2): 377–416.

Grobovšek, Jan. 2015. "Managerial Delegation, Law Enforcement, and Aggregate Productivity." Unpublished.

Guner, Nezih, Andrii Parkhomenko, and Gustavo Ventura. 2018. "Managers and Productivity Differences." *Review of Economic Dynamics* 29: 256–82.

Guner, Nezih, Gustavo Ventura, and Yi Xu. 2008. "Macroeconomic Implications of Size-Dependent Policies." *Review of Economic Dynamics* 11 (4): 721–44.

Haltiwanger, John, Ron S. Jarmin, and Javier Miranda. 2013. "Who Creates Jobs? Small versus Large versus Young." *Review of Economics and Statistics* 95 (2): 347–61.

Hendricks, Lutz, and Todd Schoellman. 2018. "Human Capital and Development Accounting: New Evidence from Wage Gains at Migration." *Quarterly Journal of Economics* 133 (2): 665–700.

Hopenhayn, Hugo A. 2014. "Firms, Misallocation, and Aggregate Productivity: A Review." *Annual Review of Economics* 6: 735–70.

Hsieh, Chang-Tai, and Peter J. Klenow. 2009. "Misallocation and Manufacturing TFP in China and India." *Quarterly Journal of Economics* 124 (4): 1403–48.

Hsieh, Chang-Tai, and Peter J. Klenow. 2014. "The Life Cycle of Plants in India and Mexico." *Quarterly Journal of Economics* 129 (3): 1035–84.

Hsieh, Chang-Tai, and Benjamin A. Olken. 2014. "The Missing 'Missing Middle.'" *Journal of Economic Perspectives* 28 (3): 89–108.

Hurst, Erik, and Benjamin Wild Pugsley. 2011. "What Do Small Businesses Do?" *Brookings Papers on Economic Activity*: 73–118.

Inglehart, R., C. Haerpfer, A. Moreno, C. Welzel, K. Kizilova, J. Diez-Medrano, M. Lagos, P. Norris, E. Ponarin, B. Puranen et al., eds. 2014. "World Values Survey: All Rounds–Country-Pooled Datafile 1981–2014." Madrid: JD Systems Institute. Version: http://www.worldvaluessurvey.org/WVSDocumentationWV.

Jasso, Guillermina, Douglas S. Massey, Mark R. Rosenzweig, and James P. Smith. 2014. "The New Immigrant Survey 2003 Round 2 (NIS-2003-2) Public Release Data." Retrieved June 16, 2016. Funded by NIH HD33843, NSF, USCIS, ASPE, and Pew. http://nis.princeton.edu.

Kaboski, Joseph P., and Robert M. Townsend. 2011. "A Structural Evaluation of Large-Scale Quasi-Experimental Microfinance Initiative." *Econometrica* 79 (5): 1357–406.

Klette, Tor Jakob, and Samuel Kortum. 2004. "Innovating Firms and Aggregate Innovation." *Journal of Political Economy* 112 (5): 986–1018.

Lagakos, David, Ahmed Mushfiq Mobarak, and Michael E. Waugh. 2018. "The Welfare Effects of Encouraging Rural-Urban Migration." Unpublished.

La Porta, Rafael, Florencio Lopez-de-Silanes, and Andrei Shleifer. 1999. "Corporate Ownership around the World." *Journal of Finance* 54 (2): 471–517.

La Porta, Rafael, Florencio Lopez-de-Silanes, Andrei Shleifer, and Robert W. Vishny. 1997. "Trust in Large Organizations." *American Economic Review* 87 (2): 333–38.

Lentz, Rasmus, and Dale T. Mortensen. 2008. "An Empirical Model of Growth through Product Innovation." *Econometrica* 76 (6): 1317–73.

Lentz, Rasmus, and Dale T. Mortensen. 2016. "Optimal Growth through Product Innovation." *Review of Economic Dynamics* 19: 4–19.

Lucas, Robert E., Jr. 1978. "On the Size Distribution of Business Firms." *Bell Journal of Economics* 9 (2): 508–23.

Luttmer, Erzo G. J. 2011. "On the Mechanics of Firm Growth." *Review of Economic Studies* 78 (3): 1042–68.

McKenzie, David, and Christopher Woodruff. 2017. "Business Practices in Small Firms in Developing Countries." *Management Science* 63 (9): 2967–81.

Midrigan, Virgiliu, and Daniel Yi Xu. 2014. "Finance and Misallocation: Evidence from Plant-Level Data." *American Economic Review* 104 (2): 422–58.

Minnesota Population Center. 2019. "Integrated Public Use Microdata Series, International: Version 7.2 [dataset]." IPUMS, Minneapolis, MN. https://doi.org/10.18128/D020.V7.2.

Moll, Benjamin. 2014. "Productivity Losses from Financial Frictions: Can Self-Financing Undo Capital Misallocation?" *American Economic Review* 104 (10): 3186–221.

MOSPI. 2012. "India: Survey on Unincorporated Non-Agricultural Enterprises (Excluding Construction), NSS 67th Round." Ministry of Statistics and Programme Implementation, Government of India. IND-NSSO-SUNAE-2010-v1.0. http://microdata.gov.in/nada43/index.php/catalog/125.

MOSPI. 2013. "India: Annual Survey of Industries 2009-10." Ministry of Statistics and Programme Implementation, Government of India. IND-CSO-ASI-2009-10-v1. http://microdata.gov.in/nada43/index.php/catalog/22.

Mueller, Holger M., and Thomas Philippon. 2011. "Family Firms and Labor Relations." *American Economic Journal: Macroeconomics* 3 (2): 218–45.

Nakamura, Emi, and Jon Steinsson. 2018. "Identification in Macroeconomics." *Journal of Economic Perspectives* 32 (3): 59–86.

Penrose, Edith Tilton. 1959. *Theory of the Growth of Firms*. New York: John Wiley and Sons.

Peters, Michael. 2020. "Heterogeneous Markups, Growth, and Endogenous Misallocation." *Econometrica* 88 (5): 2037–73.

Powell, Michael. 2019. "Productivity and Credibility in Industry Equilibrium." *RAND Journal of Economics* 50 (1): 121–46.

Restuccia, Diego, and Richard Rogerson. 2008. "Policy Distortions and Aggregate Productivity with Heterogeneous Establishments." *Review of Economic Dynamics* 11 (4): 707–20.

Rotemberg, Martin, and T. Kirk White. 2017. "Measuring Cross-Country Differences in Misallocation." Unpublished.

Roys, Nicolas, and Ananth Seshadri. 2014. "Economic Development and Organization of Production." Unpublished.

Schoar, Antoinette. 2010. "The Divide between Subsistence and Transformational Entrepreneurship." In *Innovation Policy and the Economy,* Vol. 10, edited by Josh Lerner and Scott Stern, 57–81. Chicago: University of Chicago Press.

Ulyssea, Gabriel. 2018. "Firms, Informality, and Development: Theory and Evidence from Brazil." *American Economic Review* 108 (8): 2015–47.

United States Census Bureau. 2016. "Business Dynamics Statistics." United States Department of Commerce. https://www.census.gov/programs-surveys/bds.html.

Xi, Xican. 2016. "Multi-Establishment Firms, Misallocation and Productivity." Unpublished.