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

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A Theoretical Appendix

A.1 Static Equilibrium

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

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

which implies $w_P = Q \equiv \exp\left[\int_0^1 \ln q_j dj\right]$. The production function [see equation (3)] also implies that

$$L^P = \int_0^1 l_j dj = \int_0^1 \frac{y_j p_j}{q_j p_j} dj = \frac{Y}{w} \int_0^1 \mu_j^{-1} dj, \tag{1}$$

where L^P is the aggregate demand for production labor. Using that $\mu_j = \frac{1}{1-e(n_j)^\sigma}$, where n_j is the number of products the producer of product j has in its portfolio, (1) implies that $L^P = \frac{1}{\mathcal{M}} \frac{1}{\omega_P}$, where $\omega_P = \frac{w_P}{Y}$ and $\mathcal{M}$ is given by

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

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

A.2 Firm Size Distribution

Let $\nu_{n,t}^H$ denote the share of high-type firms with n products, and F_t^j be the number of firms of type j. Then, firm size distribution of the economy can be represented by the following differential equations:

$$\frac{\partial F_t^H \nu_{1,t}^H}{\partial t} = z_t \times \delta - F^{H,t} \nu_{1,t}^H \tau_{H,t} \tag{2}$$

$$\frac{\partial F_t^H \nu_{n,t}^H}{\partial t} = \left[\nu_{n-1,t}^H (n-1) x_{n-1,t} + \nu_{n+1,t}^H \tau_{H,t} (n+1) - \nu_{n,t}^H n (\tau_{H,t} + x_{n,t})\right] \times F_t^H. \tag{3}$$

$$\frac{\partial F_t^L}{\partial t} = z_t \times (1-\delta) - F^{L,t} \tau_{L,t}. \tag{4}$$

and the requirement that $\nu_{n,t}^H$ be a proper distribution, $\sum_{n=1}^{\infty} \nu_{n,t}^H = 1$.

Equation (2) states that the number of one-product high type firms is given by the difference between entering high-type firms and exiting high-type firms. Recall that $\tau_{j,t}$ denotes the rate at which a firm of type j loses a given product at each point in time. Similarly, equation (3) is an accounting equation for the net-change in the number of high type firms with n products. Finally, (4) is the analogue of (2) for low-type firms, which always have a single product.

Proposition 1 *Consider a stationary equilibrium and let the flow of entry z and high-type firms' expansion rates $\{x_n\}_{n=1}^{\infty}$ at stationary equilibrium be given. The distribution of high-type firms is*

$$\nu_n^H = \frac{n^{-1}\frac{\tau_H}{x_n}\prod_{j=1}^{n}\left(\frac{x_j}{\tau_H}\right)}{\sum_{s=1}^{\infty} s^{-1}\frac{\tau_H}{x_s}\prod_{j=1}^{s}\left(\frac{x_j}{\tau_H}\right)}, \tag{5}$$

the measure of high- and low-type firms is

$$F^H = \frac{\delta z}{\tau_H} \times \left[\sum_{n=1}^{\infty}\frac{\tau_H}{n x_n}\prod_{j=1}^{n}\left(\frac{x_j}{\tau_H}\right)\right] \quad \textit{and} \quad F^L = \frac{(1-\delta)z}{\tau_L}, \tag{6}$$

the aggregate rate of creative destruction is

$$\tau = z \times \left[\delta\sum_{s=1}^{\infty}\prod_{j=1}^{s}\left(\frac{x_j}{\tau_H}\right) + 1\right], \tag{7}$$

and the type-specific creative destruction rates are

$$\tau_H = \tau - z\left(1-\delta\right)\left(\frac{\beta-1}{\beta}\right) \quad \textit{and} \quad \tau_L = \beta\tau - z\left(1-\delta\right)\left(\beta-1\right). \tag{8}$$

Proof. By setting the time derivatives to zero in (2), (3) and (4), stationary firm size distribution is described by the following equations

$$\begin{aligned} F^H\nu_1^H\tau_H &= z\times\delta & (9)\\ \nu_n^H n\left(\tau_H + x_n\right) &= \nu_{n-1}^H\left(n-1\right)x_{n-1} + \nu_{n+1}^H\tau_H\left(n+1\right) & (10)\\ F^L\tau_L &= z\times\left(1-\delta\right) & (11)\end{aligned}$$

Let ν_1^H and τ be given. First note that consistency requires that the total amount of innovation has to be equal to the total rate of creative destruction:

$$\tau = \tau_H(1-F^L) + \tau_L F^L \tag{12}$$

Then, by using (11), (12) and $\tau_L = \beta\tau_H$, we get

$$\tau_H = \tau - z\left(1-\delta\right)\left(\frac{\beta-1}{\beta}\right) \quad \text{and} \quad \tau_L = \beta\tau - z\left(1-\delta\right)\left(\beta-1\right). \tag{13}$$

Next, by using (9) - (11), we calculate F^L, F^H, and $\{\nu_n\}_{n=2}^{\infty}$.

Lemma 1 *The distribution of high types takes the following form*

$$\nu_n^H n = \frac{\prod_{j=1}^{n} x_j}{\tau_H^n}\frac{\tau_H}{x_n}\nu_1^H. \tag{14}$$

Proof. Substituting (14) in (9) - (11) shows that if ν_n^H satisfies (14), it satisfies all the flow equations in (9) - (11). ■

This implies that $1 = \sum_{n=1}^{\infty} \nu_n^H = \nu_1^H \sum_{n=1}^{\infty} \frac{1}{n} \frac{\tau_H}{x_n} \prod_{j=1}^{n} \left(\frac{x_j}{\tau_H}\right)$, so that (14) reads

$$\nu_n^H = \frac{1}{n} \frac{\prod_{j=1}^{n} x_j}{\tau_H^n} \frac{\tau_H}{x_n} \frac{1}{\sum_{s=1}^{\infty} \frac{1}{s} \frac{\tau_H}{x_s} \prod_{j=1}^{s} \left(\frac{x_j}{\tau_H}\right)}. \tag{15}$$

Then, from (9) and (11), we have

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

Hence, we only need to determine τ, which we get from (19) as

$$\tau \;=\; \sum_{n=1}^{\infty} n x_n \nu_n^H F^H + z = \left[\sum_{n=1}^{\infty} \delta \left(\prod_{j=1}^{n} \left(\frac{x_j}{\tau_H}\right)\right) + 1\right] z. \tag{16}$$

Together with (13), one can show that (16) has a unique solution for τ. ■

A.3 Derivation of Equation (21)

We can express $\ln Q_t$ after an instant Δt as

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

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

$$g_t = \frac{\dot{Q}_t}{Q_t} = \lim_{\Delta t \to 0} \frac{\ln Q_{t+\Delta t} - \ln Q_t}{\Delta t} = \ln\left(\gamma_t\right) \tau_t.$$

A.4 Stationary Equilibrium of the Model

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

Step 1 Fix $s \equiv (n^*, \omega_P)$ where n^* and ω_P are delegation cut-off and normalized wage rate for production workers, respectively. By using (7) and (8), we can write the rate of destruction for high types $\tau_H(s)$ as

$$\tau_H(s) = z(s) \times \left\{\left[\delta \sum_{h=1}^{\infty} \prod_{j=1}^{h} \left(\frac{x_j(s)}{\tau_H(s)}\right)\right] + 1 - (1-\delta)\left(\frac{\beta - 1}{\beta}\right)\right\}, \tag{17}$$

where $[x_j(s)]_{j=1}^{\infty}$ is the optimal innovation policy by high types implicitly defined in (13) and $z(s)$ is the optimal entry rate. We focus on a solution where $x_j < \tau_H$ for all τ_H. This is a sufficient condition for a stationary solution.[1] We will show below that such a solution exists for all s provided that θ_E is large enough.

[1] A necessary condition is that there exists $\hat{n}$ with $x_j < \tau_H$ for all $j > \hat{n}$.

Let $v_H(n)$ be normalized value function (normalized with Y_t) of a high-type firm depicted in (13).[2] At BGP where both C_t and Y_t grows at the same rate and $\dot{v}_{H,t} = 0$, it can be written as

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

where we use the fact that $w_p = Q$ to substitute $\frac{Q}{Y}$ with ω_P and $r = \rho + g$ from household problem.[3] By rearranging terms and explicitly imposing the restriction $x_j < \tau_H$, we can write v_H as

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

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

$$b(n) = \max_{x_n < \tau_H} \left\{ h(n, x_n) + \frac{x_n(n+1)}{\rho + (x_n + \tau_H)n} b(n+1) + \frac{\tau_H(n-1)}{\rho + (x_n + \tau_H)n} b(n-1) \right\}, \tag{18}$$

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

We will show that the right-hand side of (18) satisfies Blackwell's sufficient conditions for a contraction. To see this, define the operator T by

$$(Tf)(n) \equiv \max_{x_n < \tau_H} \left\{ h(n, x_n) + \frac{x_n(n+1)}{\rho + (x_n + \tau_H)n} f(n+1) + \frac{\tau_H(n-1)}{\rho + (x_n + \tau_H)n} f(n-1) \right\}. \tag{19}$$

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

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

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

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

where

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

[2] We drop the dependence of the value function on s for notational clarity.
[3] See Section A.1 for details.

Hence, the operator T satisfies the discounting condition, so that T is a contraction mapping and therefore possesses a unique fixed point [Stokey et al. (1989)], which is continuous in s and τ_H. Moreover, the expression inside the max operator in (19) is continuous in x_n and strictly concave so that Berge's Maximum Theorem implies that the set of maximizers x_n^* is a continuous function of s and τ_H. The equilibrium entry rate z is fully determined from v_H and v_L [see (17)] and hence also a continuous function of s and τ_H.[4]

Hence, equation (17) is continuous in τ_H. To see that there exists a fixed point for τ_H, note that the RHS is bounded away from zero because $z(s) > 0$ and that it is bounded from above. To see that, note that $\sum_{h=1}^{\infty} \prod_{j=1}^{h} \left(\frac{x_j(s)}{\tau_H(s)}\right)$ is bounded in a stationary equilibrium and that z is bounded [see (17)]. Hence, there exits a fixed point for τ_H. Moreover, because z is increasing in θ_E for a given s and τ_H, (17) implies that for each s there is θ_E large enough such that this fixed point satisfies $\tau_H > x_n$.

Step 2 We can now represent the whole model in terms of labor market clearing conditions. The Cobb-Douglas final good production function together with the market structure described in Section 2.1 implies that the total number of production workers hired for variety j by a producer, who is active in n markets, is given by[5]

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

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

$$H^P = \left[1 - \sum_{n=1}^{\infty} \left(\max\left\{\frac{T}{n}, \frac{T}{n^*}\right\}\right)^{\sigma} \times n \times \varphi_n\right] \times \omega_P^{-1} \tag{20}$$

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

$$H^M = \sum_{n \geq n^*}^{\infty} n \times m(n) \times \varphi_n = \left(\frac{\sigma}{\omega_M}\right)^{\frac{1}{1-\sigma}} \alpha^{\frac{\sigma}{1-\sigma}} \sum_{n \geq n^*}^{\infty} n\varphi_n - \frac{T}{\alpha} \sum_{n \geq n^*}^{\infty} \varphi_n. \tag{21}$$

Given Step 1, we can calculate the firm size distribution $\varphi_n(s) = \nu_n^H(s)F^H(s) + \nu_n^L(s)F^L(s)$ from Proposition 1. From (24), (20), and (21), the labor market clearing conditions for managers and production workers can then be written by

$$0 = \left(\frac{\vartheta - 1}{\vartheta}\mu_M\right)^{\vartheta} \left(\frac{(n^*)^{1-\sigma}\sigma\alpha}{T^{1-\sigma}\omega_P}\right)^{\vartheta-1} \frac{\vartheta}{\vartheta - 1} - \frac{T}{\alpha} \sum_{n > n*} \left(\frac{1}{n^*} - \frac{1}{n}\right) n\varphi_n(s) \tag{22}$$

$$0 = 1 - \left(\frac{\vartheta - 1}{\vartheta}\mu_M\right)^{\vartheta} \left(\frac{(n^*)^{1-\sigma}\sigma\alpha}{T^{1-\sigma}\omega_P}\right)^{\vartheta} - \frac{1}{\omega_P}\left[1 - \sum_{n=1}^{\infty} \left(\max\left\{\frac{T}{n}, \frac{T}{n^*}\right\}\right)^{\sigma} n\varphi_n(s)\right] \tag{23}$$

where two equations depend only on $s \equiv (n^*, \omega_P)$. Note that $\varphi_n(s)$ is continuous in z, τ_H and x_n. Therefore, from Step 1, left-hand-side of both equations are continuous in (n^*, ω_P). Solution to the system of equation given by (22) and (23) constitutes an equilibrium for our economy.

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

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

A.5 Transitional Dynamics with Stationary Firm Size Distribution

Proposition 2 *Suppose that the firm-size distribution at time t coincides with the stationary distribution characterized in Proposition 1. Then, for any path of the step size γ_t, there is an equilibrium path, where (i) the firm size distribution remains stationary, (ii) all aggregate variables grow at the same rate $\ln(\gamma_t)\tau_{BGP}$, where τ_{BGP} is the constant rate of creative destruction rate at the stationary equilibrium.*

Proof. Note that in the stationary equilibrium of the model, the step size γ_t does not affect any expressions. Hence, we need to show that there exists an interest rate path r_t such that C_t, Q_t and Y_t grow at the same rate during the transition. If this was the case, firms' innovation and entry choices would not change and the distribution would remain stationary. It is easy to see that interest rate path

$$r_t = \ln(\gamma_t)\tau_{BGP} + \rho$$

serves the purpose. Recall that consumption decisions of the household yield the usual Euler equation which implies that

$$r_t = g_{C,t} + \rho$$

so that under the proposed interest rate path, $g_{C,t} = \ln(\gamma_t)\tau_{BGP}$. Moreover $g_{Q,t} = \ln(\gamma_t)\tau_{BGP}$ as shown in Appendix A.3. Lastly we have $Y_t = Q_t \mathcal{M}_t L_{P,t}$. Since $\mathcal{M}_t$ and $L_{P,t}$ are constant at the proposed equilibrium, this implies that $g_{Y,t} = g_{Q,t}$. Therefore all growing variables grows at the same rate. ■

A.6 A Simple Microfoundation for α

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

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

While the manager's effort choice is not contractible, the entrepreneur can monitor the manager to prevent him from shirking. If the entrepreneur spends s units of her time monitoring the manager, she will catch a shirking manager with probability s. Whenever the manager shirks and gets caught, the entrepreneur can go to court and sue the manager for the managerial wage w. In particular, the court (rightly) decides in the entrepreneur's favor with probability κ. Hence one can think of κ as parameterizing the efficiency of the legal system. Finally, the demand for shirking arises because shirking carries a private benefit bw, where $b < 1$.[6]

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

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

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

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

is therefore given by[7]

$$e_j = \frac{T}{n} - m_j s + \eta m_j \quad = \quad \frac{T}{n} + \left(\eta - \frac{b}{\kappa}\right) \times m_j = \frac{T}{n} + \alpha\left(\kappa, \eta, b\right) \times m_j. \tag{24}$$

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

B Empirical Appendix

B.1 Data

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

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

For our analysis, we utilize the following four moments from the U.S. data: (i) the cross-sectional relationship between age and size, which we refer to as the life-cycle, (ii) the aggregate employment share by age, (iii) the exit rate as a function of age *conditional on size*, and (iv) the rate of entry. For our main analysis we focus on establishments. The BDS reports both aggregate employment and the number of establishments by age. This allows us to calculate the first two moments. The BDS also directly reports both entry and exit rates for each size-age bin. The entry rate at the establishment level is calculated as the number of new establishments at time t relative to the average number of establishments in t and $t-1$. Similarly, the exit rate at the establishment level is calculated as the number of exiting establishments in t relative to the average number of establishments in t and $t-1$. The corresponding information is also reported at the firm level. In particular, the BDS reports the number of exiting firms for different size-age bin. Note that all establishments owned by the firm must exit for the firm to be considered an exiting firm. As for firm entry, we treat firms of age 0 as an entering firm. Because a firm's age is derived from the age of its establishments, this implies that we treat firms as entering firms only if all their establishments are new. In Section B.5, we provide detailed descriptive statistics about the dynamic process at both the firm- and establishment-level.

Establishment-Level Information for India As explained in the main body of the text, we construct a representative sample of the Indian manufacturing sector by combining data from the Annual Survey of Industries (ASI,MOSPI (2013b)) and the National Sample Survey (NSS, MOSPI (2012a)), which - every five years - has a special module to measure unorganized manufacturing establishments. We use cross-sectional data from 2010. In contrast to the U.S., both the ASI and NSS are based on establishments and we cannot link establishments to firms. With the majority of

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

employment being accounted for by very small producers, multi-establishment firms are unlikely to be important for the aggregate in India. Firms in the NSS account for 99.2% of all establishments and for 76% of manufacturing employment. In Table 1 we report the size distribution of establishments in the NSS. More than 80% of plants have at most 2 employees and only 5% have more than 5 employees. Note that the NSS data contains some large firms: 1.5% of plants have more than 10 employees and roughly 0.25% have more than 20 employees. These plants are sampled in what is called "Segment 9" of the data, which is reserved for such large firms.

Table 1: The employment distribution in the NSS

Number of employees							
1-2	3-5	6-9	10-14	15-19	20-24	25-49	>50
82.10%	13.49%	2.90%	0.87%	0.36%	0.11%	0.10%	0.05%

Notes: The table reports the share of firms in the respective size category in the NSS data in 2010. We use the sampling weights provided in the data to aggregate the number of firms.

Comparison of the NSS/ASI Data with the Economic Census In our analysis we follow the literature to treat the combination of the NSS and ASI data as measuring the population of firms (see for example Hsieh and Olken (2014) or Hsieh and Klenow (2014)). To provide further evidence for the validity of this choice, we now compare this data to the Indian Economic Census (EC) (MOSPI (2005, 2013a)). The EC is a complete count of all economic units in the country. While the ASI/NSS is collected in the year 2010, no EC was conducted in 2010. We therefore report a comparison with the EC in 2005 and 2013. Given that the ASI/NSS focuses on manufacturing plants, we also select manufacturing firms from the EC.

In Table 2 we compare the firm size distribution as measured by these three datasets. We report the share of plants, the share of employment and the average plant size for different size categories. The main take-away from Table 2 is that the distributions from the EC and our ASI/NSS are very similar. There are slightly more firms with 1-4 employees in our ASI/NSS sample and hence their aggregate employment share is consequentially also larger. Note however, that the ASI/NSS sample contain less firms and therefore less employment in the 5-9 category. The share of firms and employment in firms with less than 10 employees is almost identical between the EC and the NSS/ASI data. Also note that the distribution of average firm size within size classes is very similar.

Non-homothetic Demand for Outside Managers In Figure 1 we provide additional evidence for the non-homothetic pattern of managerial demand reported in Table 2. While Table 2 is based on firm-level data, Figure 1 uses individual data from IPUMS (for India) and the Current Population Survey (the U.S). In both datasets we observe individuals occupation, whether they work as a wage worker and the size of the firm in which they work. Hence, we can compute the share of people who are classified as outside managers conditional on working in firms in a particular size bin.

The left panel of Figure 1 shows that the non-homotheticity of managerial demand is not only present in the firm-level data but also pervasive in the data from IPUMS. The results are also (roughly) quantitatively in line with our measurement from the firm-level data reported in Table 2. The right panel documents the same relationship for the U.S. Again, we find robust evidence for managerial demand to be non-homothetic. Note that the share of outside managers in the CPS data is quantitatively similar to what we measure IPUMS. There we found a managerial share of 12.5%. Note also that our model predicts that the non-homotheticity should be less pronounced in the U.S., where the delegation efficiency α is high relative to the owners' managerial supply T - see

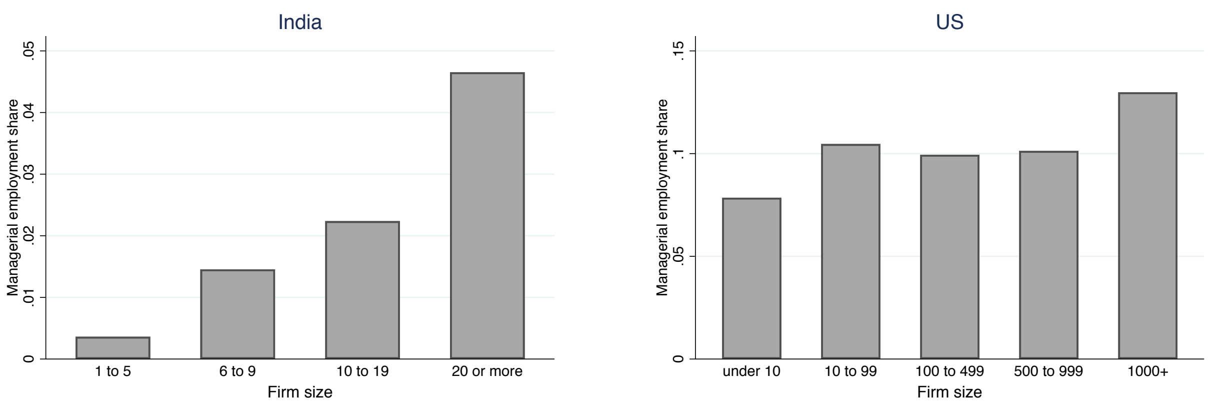
Table 2: Comparison of NSS/ASI and Economic Census

Size	Share of firms			Share of employment			Average firm size		
	EC '05	EC '13	ASI/NSS	EC '05	EC '13	ASI/NSS	EC '05	EC '13	ASI/NSS
1-4	89.82%	90.08%	92.97%	49.01%	49.26%	54.76%	1.7	1.6	1.6
5-9	8.24%	7.88%	4.91%	17.24%	16.12%	11.61%	6.5	6.0	6.3
10-19	0.93%	1.05%	1.43%	3.92%	4.54%	7.04%	13.1	12.8	13.0
20-49	0.55%	0.60%	0.42%	5.19%	5.95%	4.58%	29.3	29.5	29.1
50-99	0.24%	0.22%	0.13%	5.19%	4.91%	3.56%	67.6	67.0	69.9
100-249	0.16%	0.11%	0.09%	7.45%	5.66%	4.86%	142.0	146.5	149.3
250-499	0.04%	0.03%	0.03%	4.70%	3.83%	3.56%	329.8	336.1	346.7
500-999	0.01%	0.01%	0.01%	2.87%	3.35%	3.41%	664.3	678.7	683.9
1000+	0.01%	0.01%	0.01%	4.43%	6.38%	6.61%	2208.1	2256.3	2452.7

Notes: This table contains summary statistics of the firm size distribution as measured by the NSS/ASI in 2010, the Economic Census in 2005 and the Economic Census in 2013. For the NSS/ASI sample we use the sampling weights provided in the data.

e.g., equation (10).

Figure 1: Non-homothetic Demand for Outside Managers



Notes: The left (right) panel shows the share of workers working as outside managers for different firm size bin in India (the U.S.). The India data stems from IPUMS in 2004. The U.S. data stems from the CPS and we averaged the annual data for 2005-2016.

Data on Managerial Compensation and Profits for the U.S. We identify σ from the share of managerial compensation in aggregate profits *before* managerial payments [see equation (25)]. To estimate this moment, we use two data sources. From NIPA we can retrieve a measure of aggregate profits in the manufacturing industry. Specifically, we start with aggregate corporate profits, which are directly measured in NIPA (Bureau of Economic Analysis). The BEA's featured measure of corporate profits -profits from current production - provides a comprehensive and consistent economic measure of the income earned by all U.S. corporations. As such, it is unaffected by changes in tax laws, and it is adjusted for non- and misreported income. We then add to this measure non-farm proprietors' income in the manufacturing sector, which provides a comprehensive and consistent economic measure of the income earned by all U.S. unincorporated non-farm businesses.

To measure managerial wages, we augment the information in NIPA from information in the census. While NIPA reports compensation for workers, managerial payments are not directly recorded in NIPA. To calculate the managerial wage bill, we therefore use the U.S. census data. In the census we have micro data on labor compensation and occupations at the micro level. Hence, we calculate the *share* of managerial payments in the total wage bill and apply that share to the aggregate compensation data in NIPA. According to the census, managerial compensation amounts to roughly 22% of total wages. Recall that the managerial employment share in the U.S. is about 12.5% so that managerial wages are relatively high. We then calculate the share of managerial compensation (CSM) in aggregate profits net of managerial wages as

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

where "Managerial Compensation" is simply 22% of the total labor compensation in NIPA. We also calculate a second measure of CSM, where we do not include "Nonfarm Proprietor's Income." We calculate CSM before the Great Recession, because we were concerned about corporate profits being very low during the financial crisis. CSM is quite volatile. It ranges from 65% in 2001 to 33% in 2006. For our calibration we focus on the average across the years 2000 - 2007, which is 50%. If we do not include "Nonfarm Proprietor's Income", the numbers are very similar and only slightly larger, ranging from 69% in 2001 to 35% in 2006. The average is 53%. Hence, it is not essential for us to take "Nonfarm Proprietor's Income" into account.

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

The list of occupations according to ISCO is contained in Table 3. To qualify as a manager in the sense of our theory, two characteristics have to be satisfied. First, the respective individual has to work as a "Legislator, senior official, and manager." In order to focus on managers, which are agents of a firm owner, i.e., outside managers, we *also* require workers to be wage workers and not working on their own account or to be unpaid family members. This information is also contained in the IPUMS census data in the variable "worker type." As we showed in Table 1 above, it is important to take these differences into account as poor countries have a higher share of people working on their own account (or as a family member) *conditional* on being classified as a manager according to ISCO.

Table 3: List of Occupations according to ISCO

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

Notes: Table 3 contains the occupational categories available in the IPUMS data (https://international.ipums.org/international-action/variables/OCCISCO). A necessary condition for someone to be classified as an outside manager is to be assigned the occupational title "Legislators, senior officials, and managers." See the main body of the text for the additional requirements.

B.2 Identification of the Model

We will now discuss the identification of our model in more detail. In total, there are 11 parameters to identify[8]:

$$\Omega \equiv \{\alpha, \sigma, T, \mu_M, \vartheta, \theta, \theta_E, \delta, \beta, \gamma^{US}, \lambda\}.$$

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

We then use several moments related to managerial employment patterns - namely the compensation of managers relative to corporate profits, the entrepreneurial share in total compensation, the dispersion of managerial wages, and managerial employment shares - to identify σ, T, ϑ, α and μ_M. Consider first σ, the elasticity of profits with respect to managerial services.[9] In the model, the total compensation for managerial personnel relative to aggregate profits (before managerial payments) is given by

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

where $\varphi_n = F^H v_n^H$ and $\varphi_1 = F^H v_1^H + F^L$ is the endogenous firm size distribution. By using $m(n) = T\alpha^{-1} \times \max\left\{0, (n^*)^{-1} - (n)^{-1}\right\}$, $\omega_M \equiv \frac{w_M}{Y} = \sigma\alpha\left(\frac{n^*}{T}\right)^{1-\sigma}$ and $e(n) = T\max\left\{n^{-1}, (n^*)^{-1}\right\}$, we get that

$$\frac{w_M H^M}{\Pi + w_M H^M} = \sigma \frac{\sum_{n=1}^{\infty} (n^*)^{1-\sigma}\left(\max\left\{0, \frac{1}{n^*} - \frac{1}{n}\right\}\right) \times n \times \varphi_n}{\sum_{n=1}^{\infty}\left(\max\left\{\frac{1}{n}, \frac{1}{n^*}\right\}\right)^{\sigma} \times n \times \varphi_n}. \tag{25}$$

Hence, conditional on n^* and the firm size distribution, (25) only depends on σ.

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

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

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

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

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

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

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

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

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

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

Finally, we identify α and μ_M by using the share of managers in the whole economy *and* among Indian immigrants to the U.S. economy. Let χ denote the equilibrium managerial employment share which is given by

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

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

$$\mu_M \alpha = (\chi)^{-\frac{\vartheta-1}{\vartheta}} \times \sum_{n \geq n^*}^{\infty} T\left(\frac{1}{n^*} - \frac{1}{n}\right) \times n \times \varphi_n. \tag{26}$$

Hence, given n^*, T, ϑ, and φ_n, we can directly determine $\mu_M \times \alpha$ from the data on the share of managers in the whole population (i.e., χ). To separate the effect of managerial human capital (μ_M) from delegation efficiency (α), we use data on managerial employment pattern of Indian immigrants. Because our approach uses additional data and because all allocations in the model only depend on $\mu_M \times \alpha$, we discuss the details of our strategy in Section B.2.2. Once we identify μ_M, we get α from (26).

Lastly we use moments regarding aggregate dynamics of the economies to pin down γ and λ. In particular, we calibrate the step-size for U.S., γ^{US}, to fit the aggregate growth rate as $g = \ln\left(\gamma^{US}\right)\tau$ and U.S. is assumed to be on the balanced growth path. In the case of India, step size is partly determined by the productivity gap between U.S. and India and λ parametrizes the importance of this channel on step size [see (30)]. By using (21) and (30), we can write the *change* of relative productivity differences $Z_t \equiv \frac{Q_{US,t}}{Q_{IND,t}}$ as

$$g_{Z,t} = \frac{\dot{Z}_t}{Z_t} = \left\{\ln(\gamma^{US}\tau_{US,t} - \tau_{IND,t}\left[\ln(\gamma^{US}) + \lambda\ln(Z_t)\right]\right\} \tag{27}$$

Therefore, given γ^{US} and the aggregate rates creative destruction for U.S. and India, we can infer λ from the dynamics of relative productivity differences between the U.S. and India.

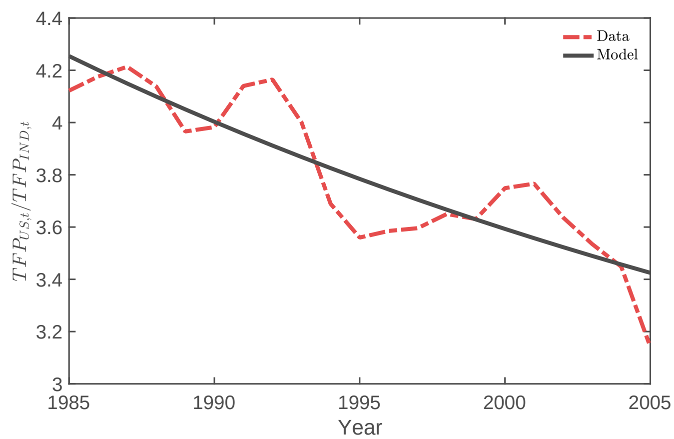
To relate Z_t to the data, note that empirically we observe total factor productivity as implied by the Penn World Tables. Given that total population size is normalized to unity, our model implies that TPF is given by $TFP = Y = Q\mathcal{M}L^P$ (see (6)). Hence, relative TFP is given by

$$\frac{TFP_{t,US}}{TFP_{t,IND}} = Z_t \times \frac{\mathcal{M}_{t,US}L^P_{t,US}}{\mathcal{M}_{t,IND}L^P_{t,IND}}.$$

Note that if the firm-size distribution is stationary, both $\mathcal{M}_{t,c}$ and the sectoral allocation of labor $L^P_{t,US}$ are constant. Hence, the change in measured relative TFP, $TFP_{t,US}/TFP_{t,IND}$, is exactly $g_{Z,t}$ given in (27) and hence can be used to calibrate λ.

In Figure 2 we depict the evolution of relative TFP levels between the U.S. and India between 1985 and 2005. It is clearly seen that India is catching up as relative TFP differences decline from 4 in 1985 to roughly 3.2 in 2005. We therefore calibrate λ and level of relative productivity in 1985, Z_{1985}, to minimize the distance (as measured by the sum of squared residuals) between the model and the data. The resulting fit is also displayed in Figure 2.

FIGURE 2: IDENTIFICATION OF λ: TFP DIFFERENCES BETWEEN THE U.S. AND INDIA



Notes: The figure shows the observed relative TFP between the U.S. and India (dashed) and the one implied by the model (solid).

B.2.1 Identifying the managerial output elasticity σ

In this section we describe in detail how we estimate the managerial output elasticity σ using indirect inference. As explained in Section 3.2, our measure of firms' managerial environment is their total managerial services $e = T/n + \alpha \times m$ (see (7)). This object is endogenous through firms' choice of outside managers m. While e is not directly observable, we assume that it is related to the observable share of managerial practices firms adopt. We refer to the share of practices firm f adopts as MP_f. In particular, we assume that e and MP_f are related via the measurement equation $e_f = \upsilon MP_f^{\varrho}$. As explained in Section 3.2, we can use the pre-treatment information on the share of adopted practices in the U.S. and India and the model-implied differences in e in our U.S. and India calibration to identify ϱ. Given ϱ, we can then express the model-implied change in total managerial services e due to the treatment, e^{Treat}_{IND}, as a function of observables $(MP_{IND}, MP_{US}, MP^{Treat}_{IND})$ and the equilibrium objects in our calibration (e_{IND}, e_{US}) - see equation (27). In our baseline calibration, we infer that the treatment increased total managerial efficiency among treatment plants by 26% (see footnote 19).

Because e is endogenous, we have to take a stand *how* the experiment induced firms to increase e by 26%, i.e., which structural parameter changed. We assume that the experiment increases the total efficiency of managerial services e by a multiple $\xi > 1$. Hence, if a treatment firm hires m units of managerial human capital on the market, it generates $\xi e = \xi(T/n + \alpha \times m)$ units of managerial services in the firm. This formalization captures the main spirit of the experiment in that the intervention provided information about how to make management more efficient via the provision of consulting services, but left the actual adoption of such managerial practices up to the treatment firms.

In practice we implement this procedure in the following way. Given the partial equilibrium nature of the experiment, treatment firms chose their optimal quantity of efficiency units of outside managers according to (8) taking the higher return to managerial services ξ as given. Formally, the optimal number of outside managers treatment firms hire, $m(\xi)$, is implicitly defined by

$$\left[m_j(\xi)\right]_{j=1}^{n} = \underset{m_j \geq 0}{\operatorname{argmax}} \sum_{j=1}^{n} \left\{ \left(\xi \left(\frac{T}{n} + \alpha m_j \right) \right)^{\sigma} Y - w_M m_j \right\}. \tag{28}$$

The solution to this problem is given by (see (10))

$$m(n;\xi) = \left(\frac{\sigma}{\omega_M} \right)^{\frac{1}{1-\sigma}} (\xi\alpha)^{\frac{\sigma}{1-\sigma}} - \frac{1}{\alpha}\frac{T}{n} \tag{29}$$

and the associated number of managerial services, $e(n;\xi)$ is given by

$$e(n;\xi) = \xi(T/n + \alpha m(n;\xi)) = \left(\frac{\xi\alpha\sigma}{\omega_M} \right)^{\frac{1}{1-\sigma}}. \tag{30}$$

This implies that

$$\frac{e_{IND}^{Treat}}{e_{IND}} = \frac{e(n;\xi)}{e(n)} = \frac{(\xi\alpha\sigma/\omega_M)^{\frac{1}{1-\sigma}}}{(\alpha\sigma/\omega_M)^{\frac{1}{1-\sigma}}} = \xi^{1/(1-\sigma)}, \tag{31}$$

so that the required productivity increase ξ for treatment firms to increase their level of managerial efficiency from e_{IND} to e_{IND}^{Treat} is given by $\xi = \left(\frac{e_{IND}^{Treat}}{e_{IND}} \right)^{1-\sigma}$.

To understand our strategy to estimate the σ, suppose that all other structural parameters were given. In this hypothetical case, where we would only estimate σ, our algorithm would be the following:

1. Guess a value of σ and solve the equilibrium of the model.
2. The model then implies equilibrium values for e_{IND} and e_{US}.
3. Given (e_{IND}, e_{US}), an assumption on the adoption of such managerial practices in the U.S., MP_{US} and the estimated increase in managerial practices for treatment firms, $\frac{MP_{IND}^{Treat}}{MP_{IND}}$, we can use (27) to calculate e_{IND}^{Treat}
4. Given e_{IND}^{Treat}, we can calculate ξ according to $\xi = \left(\frac{e_{IND}^{Treat}}{e_{IND}} \right)^{1-\sigma}$
5. Given ξ we then perform the management experience in our model.
   (a) We select 100 firms (50 for the treatment and 50 for the control group) from the top 0.01% of the size distribution from our India calibration. This selection procedure based on size mimics the selection procedure in Bloom et al. (2013), who note that the experimental firms had "about 270 employees, assets of 13 million, and sales of 7.5 million a year. Compared to U.S. manufacturing firms, these firms would be in the top 2% by employment and the top 4% by sales, and compared to India manufacturing they are in the top 1% by both employment and sales (Hsieh and Klenow 2010)" (Bloom et al., 2013, p. 9). Because we calibrate our model to the population of Indian firms (i.e. including firms in the NSS), firms with 270+ employees correspond to the top 0.01% of the firm size distribution. Our calibrated model implies that this set of firms coincides with firms of $n = 7$ products.

(b) We then scale the total managerial efficiency of treatment firms by ξ to induce the required increase in managerial efficiency e and simulate their life-cycle for 100 weeks. Note that treatment firms are free to change their number of outside managers at any point at the equilibrium wage rate w_M of the baseline economy to mimic the partial equilibrium nature of the experiment. For the entire 100 weeks, managerial services in treatment firms have a productivity advantage of ξ.

(c) We then measure profits for all 100 weeks according to (8) for both treatment and control firms. For control firms, profits gross of innovation spending are given by (25). For treatment firms, profits are given by

$$\tilde{\pi}^{Treat}(n) = (1-\sigma)\, e\,(n;\xi)^{\sigma}\, n + e\,(n;\xi)^{-(1-\sigma)}\, \sigma\xi T.$$

Hence, treatment firms have higher profits for three reasons: (1) they hire more managerial service given their size ($m\,(n;\xi) > m\,(n)$), (2) they receive a direct benefit of being able to use e more efficiently ($\xi > 1$) and (3) they will on average be larger as their innovation incentives increase. While (1) and (2) are static effects, (3) is a dynamic effect

6. Given the model-generated data on $\tilde{\pi}^{Treat}(n)$ and $\tilde{\pi}(n)$ we then run the regression in (26), i.e. we estimate the specification

$$\ln \tilde{\pi}_{i,t} = \beta_0 + \beta_1 \times TREAT_{i,t} + \epsilon_{i,t} \tag{32}$$

and recover the treatment effect $\hat{\beta}_1$. Note that in our regression there is no need to use firm-fixed effects as all firms with $n > 1$ are high-type firms and all firms have the same size n. As explained in Section 3.2 we choose profits as our measure of firm-performance, while Bloom et al. (2013) focus on physical output. Bloom et al. (2013) do not estimate a treatment effect based on profits.

7. To average out the sampling variation in our estimate, we replicate this procedure 250 times and calculate the model-implied treatment effect

$$\hat{\beta}^{Treat} = \frac{1}{250}\sum_{i=1}^{250} \hat{\beta}_1^{(i)}. \tag{33}$$

8. If $\hat{\beta}^{Treat}$ is equal to the empirically observed value of 9%, we stop. Otherwise we go back to step 1 with a different guess for σ.

Recall that in order to infer e_{IND}^{Treat}, we had to assume a particular value for the share of practices adopted by firms in the U.S., MP_{US} (see (27)). For our baseline calibration, we assumed that firms in the U.S. adopt all such practices as these practices "have been standard for decades in the developed world" (Bloom et al., 2013, p. 43). From the experimental micro-data, we can provide some additional evidence for this assumption. In the experimental data for Indian firms, we observe two objects related to the firms' managerial environment: the share of particular practices the firm implements and the management score from Bloom and Van Reenen (2007). The management score is only measured pre-treatment but the practices are observed pre- and post-treatment. Using the pre-treatment variation of managerial practices and managerial scores across the Indian firms and the estimated changes in managerial practices due to the treatment, we can predict the average change in the firms' managerial score induced by the intervention. More specifically, we first run the cross-sectional regression

$$BVR_f = \beta + \gamma \times MP_f + \epsilon_f, \tag{34}$$

where BVR_f is the management score from Bloom and Van Reenen (2007) and MP_f is the share of adopted managerial practices. We then predict the change in the BVR score due to the treatment according to

$$E[BVR_f|Treatment] = E[BVR_f] + \hat{\gamma} \times \left(E[MP_f|Treatment] - E[MP_f]\right), \tag{35}$$

where $\hat{\gamma}$ is estimated coefficient from (35). The average BVR score among Indian firms before the treatment is 2.6. Using the estimated coefficient $\hat{\gamma}$ and the change in managerial practices due to the treatment $E[MP_f|Treatment] - E[MP_f]$, we find that the treatment increases the BVR score among treatment firms, $E[BVR_f|Treatment]$, depending on how we treat outliers in the regression, to 2.84 on the low end and 3.12 on the high end. The average BVR score among U.S. firms is equal to 3.28. Hence, this exercise suggests that the treatment closes the "management gap" as measured by BVR scores by $\frac{2.84-2.6}{3.28-2.6} = 35\%$ on the low end and $\frac{3.12-2.6}{3.28-2.6} = 76\%$ on the high end.

We can compare this number to the implications of our model. Our baseline calibration implies that the treatment increases e from $e_{IND} = 0.203$ by 26% to $e_{IND}^{Treat} = 0.255$. Our calibration also implies that $e_{US} = 0.286$. Hence, Indian firms use 71% the amount of managerial services as firms in the U.S. and the treatment increases managerial services to 89% of the U.S. level. Hence, the treatment reduces the "management gap" by $\frac{0.252-0.203}{0.286-0.203} \approx 59\%$.

B.2.2 Identifying Managerial Skill Supplies μ_M

To decompose differences in the managerial environment in India and the U.S. into supply and demand factors, we start out with 4 parameters: $(\mu_{M,US}, \alpha_{US}, \mu_{M,IND}, \alpha_{IND})$. Without loss of generality we can normalize $\mu_{M,US} = 1$. Since $\mu_{M,c} \times \alpha_c$ is identified from the equilibrium managerial employment shares [see (26)], we require one additional equation to determine the relative managerial human capital in India, $\mu_{M,IND}$. To do so, we use data on employment patterns of immigrants from India to the U.S.

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

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

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

$$\frac{\mu_{M,IND}}{\mu_{M,US}} = \underbrace{\left(\frac{\chi_{US}^M}{\chi_{US}}\right)^{1/\vartheta}}_{uncorrected\ ratio} \times \underbrace{\left(\frac{\chi_{IND}}{\chi_{IND}^M}\right)^{1/\vartheta}}_{selection\ correction\ term}. \tag{36}$$

The first term in (36) compares migrants and U.S. natives in the U.S. economy, i.e., holding α constant. Differences in managerial employment are therefore interpreted as differences in human capital. The second term accounts for selection into migration: if immigrants are positively selected on their managerial skills, i.e., $\chi_{IND}^M > \chi_{IND}$, the observed differences in outcomes in the U.S. *under*estimate the differences in skills in the population. The last term in equation (36) corrects for that potential selection.

We want to note that this identification strategy relies on occupational sorting being based on skills - both before and after migrating. If for example Indian migrants face excessive frictions to enter managerial positions (relative to other jobs), their observed managerial employment share is lower than their skills warrant. In that case we would conclude that they have relatively little human capital. See for example Hsieh et al. (2019) for an elaboration of this point. Alternatively, migrants could have been *more* likely to work as managers prior to migrating relative to their innate skills.[10] If, for example, migrants stem from families, which are richer and more likely to own a business, migrants might have worked as managers before simply because of their family connection. In that case migrants might not be selected on their managerial skill but rather representative of the population at large. If that was the case, we would erroneously conclude that the U.S. population had a comparative advantage in managerial occupations. Again we want to stress that our identification strategy will correctly recover $\alpha \times \mu$. The information in (36) is only used to separately identify α and μ.

Given that we already calibrated ϑ and we already used χ_{IND} and χ_{US} in our calibration. χ_{US}^{M} is directly observable in the U.S. Census, because we see the employment structure among recent Indian immigrants. Finally, χ_{IND}^{M} can be estimated from the New Immigration Study, which explicitly asks immigrants about the occupations *prior* to migration [see Hendricks and Schoellman (2017)].

The data to quantify (36) is contained in Table 4. Column 1 and 3 report the managerial share in the U.S. and India, respectively. In column 2 we report the managerial share among Indian immigrants in the U.S. To ensure that this population is informative about the human capital of recent Indian migrants, we restrict the sample to migrants that arrived in the U.S. within the last 5 years. The managerial share in this population is given by 12.7%. In the last column we exploit information from the New Immigration Study to measure the share of migrants that used to work as managers in India. We find that roughly 6.1% of them worked as outside manager.

Table 4: Identification of Managerial Skills: Managerial Employment Shares

	U.S.		India	
Sample	Male, 20-60 years, employed			
Population	U.S. population χ_{US}	Indian migrants χ_{US}^{M}	Indian population χ_{IND}	Indian migrants χ_{IND}^{M}
Managerial share	12.5 %	12.7 %	1.65%	6.11%
Data source	U.S. Census	U.S. Census	Indian Census	New Immigration Study

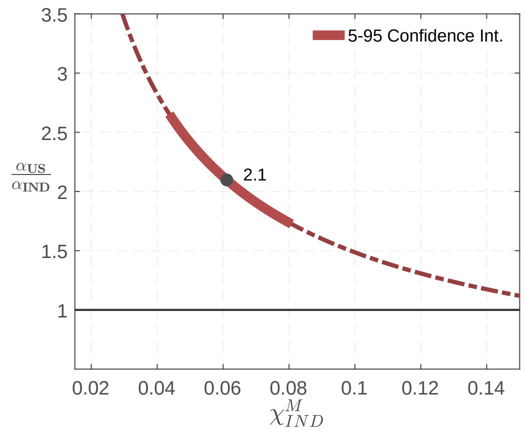
Notes The table contains estimates for the managerial employment share in the native population of the U.S. (column 1), the population Indian immigrants in the U.S. (column 2), the native population in India (column 3), and the sample of Indian migrants to the U.S. *in* India (column 4). For the definition of outsider managers, see Table 1 and the discussion there. χ_{US} and χ_{US}^{M} are calculated from the U.S. census and χ_{IND} from the Indian census. χ_{IND}^{M} is calculated from the data of the New Immigration Study. We refer to Hendricks and Schoellman (2017) for a detailed description of the data. For the New Immigration Study we use the occupational codes "10 to 430: executive, administrative and managerial" and "500 to 950: management related" as referring to managers. We also insist on the individual having received a salary (instead of, for example, being self-employed).

The sample size for estimating the managerial share of migrants in India, χ_{IND}^{M}, is only 403, i.e., quite small. To judge the robustness of our results, we report the implied differences in delegation quality $\frac{\alpha_{US}}{\alpha_{IND}}$ as a function of the point estimate of χ_{IND}^{M}. We treat the other empirical objects in (36), as fixed as these are precisely estimated. We construct the confidence intervals for $\frac{\alpha_{US}}{\alpha_{IND}}$ using a Bootstrap procedure, where we repeatedly draw samples with replacement from the New Immigration Study data and calculate χ_{IND}^{M}. The results of this exercise are contained in Figure 3. We find that the confidence interval [1.7, 2.7] contains the relative delegation efficiency of the U.S. with 90% probability. We also want to stress that this uncertainty *only* affects the decomposition of the implied counterfactual into the human capital and the delegation efficiency component, as all

[10] We are grateful to one of our referees to suggest this possibility.

allocation only depend on $\mu_{M,c}\alpha_c$.

FIGURE 3: CALIBRATING $\frac{\alpha_{US}}{\alpha_{IND}}$



Notes: The figure depicts the resulting $\frac{\alpha_{US}}{\alpha_{IND}}$ as a function of χ^M_{IND}. Our point estimate for the immigrants' managerial share in India (6.1%) yields a relative delegation quality of 2.11. The 5-to-95 confidence interval around that value ranges from about 1.7 to 2.7.

B.3 Moment Sensitivity

In Table 5 we report a sensitivity matrix, which contains the elasticity of each moment used in the internal calibration (rows) with respect to the parameters of the model (columns). Specifically, we report percentage change in the moment for a 1% change in the parameter from its benchmark calibrated value, while keeping the rest of the parameters at their benchmark values. We report the average elasticities based on +1% and -1% changes. This provides useful information about how the parameters influence the model counterpart of targeted moments. For brevity, we report the matrix for our India calibration. The sensitivity matrix for the U.S. calibration is available upon request.

TABLE 5: MOMENT SENSITIVITY

		δ	β	T	$\alpha \times \mu$	θ	θ_E	σ
M1.	Entry rate	-0.02	-0.04	0.60	0.04	0.05	1.25	-0.90
M2.	Mean empl. of 21-25-year-old firms	0.09	0.12	0.18	-0.002	0.27	0.04	-0.31
M3.	Empl. share of 21-25-year-old firms	-0.05	-0.29	-0.25	-0.04	-0.23	-0.33	0.46
M4.	Rel. exit rate of small 21-25-year-old firms	0.11	0.18	0.09	0.01	0.01	0.18	-0.13
M5.	Share of managers	0.02	0.32	0.25	1.08	0.54	-0.42	-0.89
M6.	Share of entrepreneurial profit	-0.002	-0.13	0.42	-0.03	-0.32	0.17	-0.43
M7.	Treatment effect of Bloom et al. (2013)	0.09	1.88	-1.62	-1.52	3.25	-2.44	-0.96

Notes: The table presents the elasticity for each moment used the internal calibration for India with respect to the parameters of the model. In particular, we report percentage change in the moment for a 1% change in the parameter from its benchmark value in the Indian calibration, while keeping the rest of the parameters at their benchmark values. We report the average elasticities based on +1% and -1% changes. To identify α and μ separately, we use the manager share among Indian migrants before and after emigrating to the U.S. See Section B.2.2 for more information.

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

In Section 4.2, we reported some basic patterns on managerial hiring and firm size from the Indian micro data and discussed how they relate to our theory. This section describes this analysis in more detail.

Our empirical investigation mainly focuses on the implications of the two parameters of our model: (i) entrepreneur's time endowment T and (ii) delegation efficiency α. In the theory, time endowment of entrepreneurs T has the interpretation that it can neither be sold on the market, nor is there any need to monitor. The NSS data for 1995 contain information on the size of the family of the establishment's owner (MOSPI (2012b)). As long as family members require less monitoring time than outside managers, we can think of family size as inducing variation in the time endowment T. As for the delegation efficiency α, we will rely on the variation in trust across 22 Indian states. The Indian micro data contain information about the state in which the respective establishment is located. Additionally, we extract information on the general level of trust between people at the state level from the World Value Surveys (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)). The World Values Survey is a collection of surveys based on representative samples of individuals and provides an index of trust in different regions of India. The primary index we use is derived from the answers to the question "Generally speaking, would you say that most people can be trusted, or that you can not be too careful in dealing with people?". Following Bloom et al. (2012) and La Porta et al. (1997), the regional trust index is constructed as the percentage of people providing the answer "Most people can be trusted" within the state where the firm is located. This is the most common measure of trust used in the literature. While this variable is not directly aimed at eliciting the (perceived) quality of the prevailing legal environment, it fits well into our theoretical framework as long as trust reduces the required time the owner needs to spend to incentivize outside managers. See also Bloom et al. (2012), who also use this variable to proxy the efficiency with which decisions can be delegated. In all our regressions we control for GDP pc at the state-level, which we take from National Statistics Office, Government of India (1996).

In Table 6, we look at some of the implications of our theory based on the above-mentioned proxies. We first focus on the extensive margin of managerial hiring. In the model, a firm hires an outside manager only when its size n is above a certain (endogenous) threshold which we denote as n^*

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

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

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

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

$$\mathbb{P}\left(Manager_f > 0\right) = \beta_0 + \beta_1 \log n_f - \beta_2 \log T_f + \beta_3 \log \alpha_f. \tag{37}$$

This equation implies that the likelihood of hiring a manager should be increasing in firm size and delegation efficiency and declining in the owner's time endowment. To test these predictions empirically, we estimate the coefficients of (37) by using the proxy variables mentioned above.[11] Column 1 of Table 6 summarizes the results. It suggests that the predictions of the model regarding extensive margin of managerial hiring are in line with the data: empirically large firms and firms in states with favorable trust measures are more likely to hire outside managers, while firms with larger families abstain from hiring outside managerial personnel holding firm size constant.

Table 6: Managerial Hiring, Firms Size and Growth in India

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

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

These static determinants of managerial hiring have dynamic implications relating to firms' expansion incentives and hence firm size. In particular, conditional on hiring managers, growth incentives and hence firm size are increasing in delegation efficiency. Our theory implies that delegation efficiency α and the owner's time endowment T are substitutes, i.e., we should expect a tighter link between family size and firm size in low-trust regions. Columns 2 and 3 show that this is the case. First, similar to Bloom et al. (2013), we also find a tight relationship between firm size and family size. We interpret this correlation as family members substituting for the scarcity of available outside managers. Furthermore, the coefficient on the interaction term is negative, which means that the positive relationship between firm size and family size is weaker in regions where trust is higher and hence delegation is more efficient.[12] In column 3, we replicate these results with state-fixed effects to control for all time-invariant regional characteristics.

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

[11] Note that (37) implies a linear probability model and its parameters can be estimated using OLS. We also include additional control variables in the regression. Details are given in the notes under Table 6.

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

Finally, we replicated the entire analysis of Table 6, which controlled for 2-digit sector fixed effects, with 3-sector fixed effects. The results are contained in Table 7. It is seen that results are similar. The only exception are the results in columns 2 and 3, which are conditioned on managerial hiring and hence have a small sample size[13]. While all point estimates are of the same sign, they are not significantly different from zero.

Table 7: Managerial Hiring, Firms Size and Growth in India: Robustness

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

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

B.5 Firms vs. Establishments in the U.S. Manufacturing Sector

In this section we compare the process of firm-dynamics across U.S. manufacturing firms and establishments. Table 8 provides some summary statistics about the size-distribution of firms and establishments in the U.S. The average manufacturing firm in the U.S. has 51 employees, while the average establishment only 43. It is also the case that large firms have multiple establishments (firms with more than 1000 employees have on average 13) so that large firms account for half of total employment. There is a lower concentration at the establishment level in that establishments with more than 1000 employees account for less than one-fifth of aggregate employment in manufacturing in the U.S.

We now turn to the implied dynamics. Because we focus on cross-sectional data, the information on firm (establishment) age is crucial for us. For establishments, the definition of age is straightforward. Birth year is defined as the year a establishment first reports positive employment in the LBD. Establishment age is computed by taking the difference between the current year of operation and the birth year. Given that the LBD series starts in 1976, the observed age is by construction left censored at 1975. In contrast, firm age is computed from the age of the establishments belonging to that particular firm. A firm is assigned an initial age by determining the age of the oldest establishment that belongs to the firm at the time of birth. Firm age accumulates with every additional year after that. In Figure 4 we show the cross-sectional age-size relationship for establishments (left panel) and firms (right panel) in the U.S.

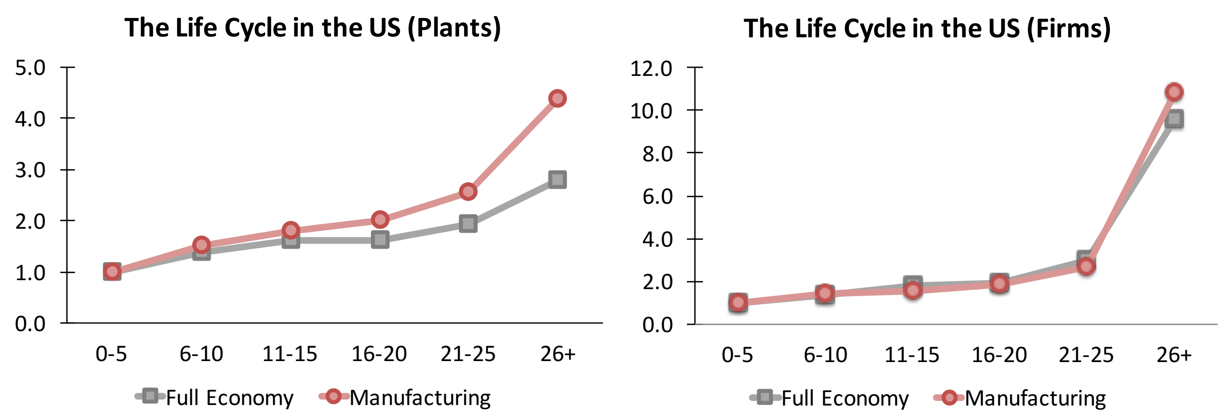
[13]Given the small sample size, finer controls for sector fixed effect leave less variation in the data for the relations we are interested in.

Table 8: Descriptive Statistics: U.S. Micro Data

Size	Firms No.	Firms Avg. Employment	Firms Agg. Share	Firms No. of Establishments	Firms Exit rate	Establishments No.	Establishments Avg. Employment	Establishments Agg. Share	Establishments Exit rate
1-4	86936	2.30	1.65	1.00	13.22	93038	2.31	1.78	16.60
5-9	48178	6.68	2.66	1.00	3.46	54281	6.73	3.02	4.20
10-19	37942	13.80	4.33	1.01	2.66	45803	14.01	5.30	3.10
20-49	32555	30.92	8.31	1.05	2.27	44085	31.90	11.62	2.40
50-99	13516	67.94	7.58	1.21	2.03	21582	71.54	12.75	1.90
100-249	8914	139.90	10.30	1.61	1.59	16476	155.76	21.20	1.00
250-499	3167	280.96	7.35	2.47	0.92	5444	348.72	15.68	0.50
500-999	1720	503.49	7.15	3.94	0.29	2120	677.19	11.86	0.30
1000+	2423	2531.92	50.67	12.68	0.25	984	2068.2	16.81	0.30
Aggregate	235351	51.44	100		6.53	283813	42.66	100	7.3

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

Figure 4: Life Cycle of Establishments and firms in the U.S.



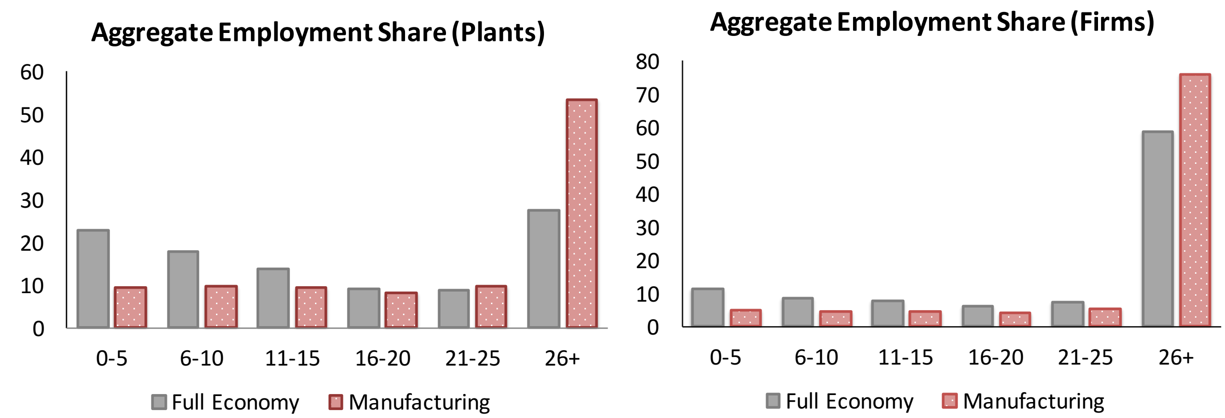
Notes: The figure contains the cross-sectional age-size relationship for establishments (left panel) and firms (right panel) in the U.S. The data are taken from the BDS and we focus on the data for 2012. We depict the results for both the manufacturing sector and the entire economy.

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

In Figure 5 we show the aggregate employment share of establishments and firms of different ages. As suggested by the life-cycle patterns in Figure 4, old firms account for the bulk of employment in the U.S. However, the relative importance of old establishments/firms is somewhat less pronounced because of exit, i.e., while the average firm/establishment grows substantially by age conditional on survival, many firms/establishments have already exited by the time they would have been 20 years old. Nevertheless, firms (establishments) older than 25 years account for 76% (53%) of employment in the manufacturing sector.

This pattern of exit is depicted in Figure 6. There we show annual exit rates for firms and establishments as a function of age. The declining exit hazard is very much suggestive of a model of

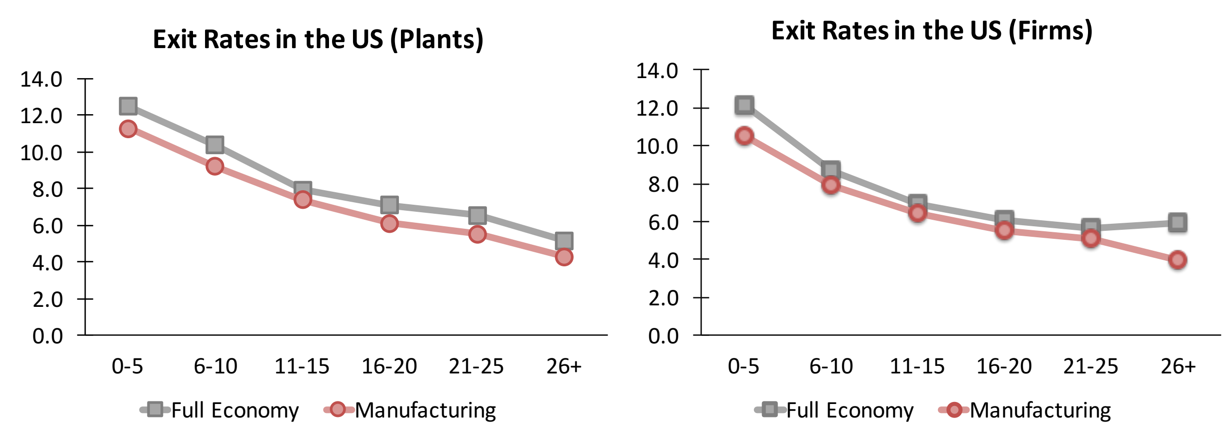
Figure 5: The employment share by age of establishments and firms in the U.S.



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

creative destruction, whereby firms and establishments grow as they age (conditional on survival) and exit rates are lower for bigger firms/establishments.

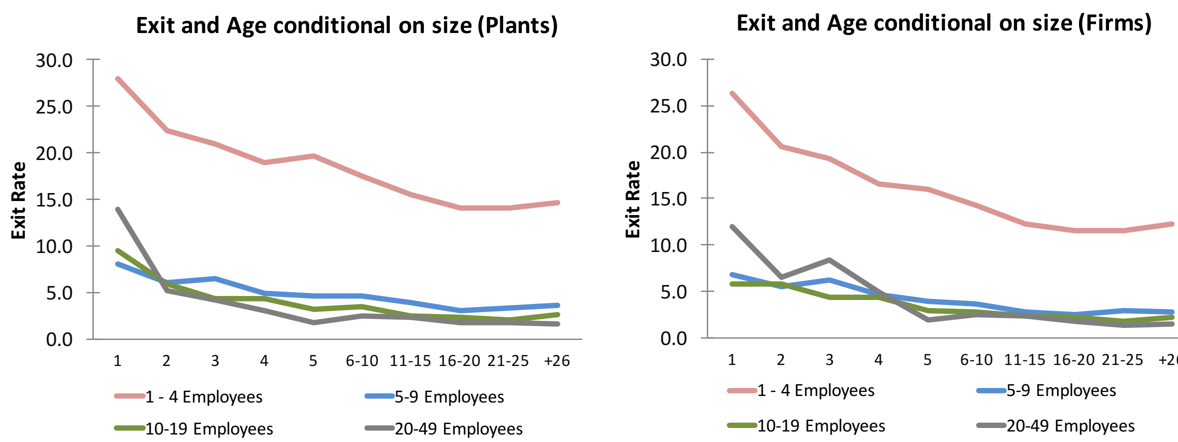
Figure 6: The Exit Rates of Establishments and Firms in the U.S. by Age



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

An important moment for us is the age-specific exit rate conditional on size. It is this moment that will identify the importance of selection. In a model without heterogeneity, size will be a sufficient statistic for future performance, so that age should not predict exit conditional on size. However, if the economy consists of high- and low-type entrepreneurs, old firms are more likely to be composed of high types conditional on size. Hence, the size-specific exit rate by age is monotone in the share of high types by age. In Figure 7 we report this schedule for both establishments and firms. The data show a large degree of age-dependence (conditional on size). The schedules for small firms and establishments look almost identical. This is reassuring because small firms are almost surely single-establishment firms, so that a firm-exit will also be a establishment-exit and vice versa.

Figure 7: Size-dependent exit rates of establishments and firms in the U.S. by age



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

B.6 Establishments in the Indian Manufacturing Sector

In this section we provide more descriptive evidence about the underlying process of firm dynamics in the manufacturing sector in India. Table 9 contains descriptive statistics for our sample of Indian manufacturing establishments. For comparison, we organize the data in the same way as in the left panel of Table 8, which contains the results for manufacturing establishments in the U.S. It is clearly seen that the establishment-size distribution in India is concentrated on very small firms. The average establishment has fewer than 3 employees and more than 50% of aggregate employment is concentrated in establishments with at most 4 employees. Such establishments account for 93% of all establishments in the Indian manufacturing sector. A comparison of establishment size distribution for the years 1995 and 2010 in Table 10 suggests that these patterns are stable over time.

Figure 8 reports the aggregate employment share by age for Indian manufacturing establishments and is hence comparable to Figure 5 for the U.S.

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

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Table 9: Descriptive Statistics: Indian Micro Data

Size	No.	Avg. Employment	Aggregate Employment Share
1-4	16047948	1.56	54.76
5-9	847889	6.26	11.61
10-19	247263	13.02	7.04
20-49	71931	29.14	4.58
50-99	23301	69.91	3.56
100-249	14899	149.31	4.86
250-499	4701	346.69	3.56
500-999	2283	683.86	3.41
1000+	1232	2452.65	6.61
Aggregate	17261448	2.65	100.00

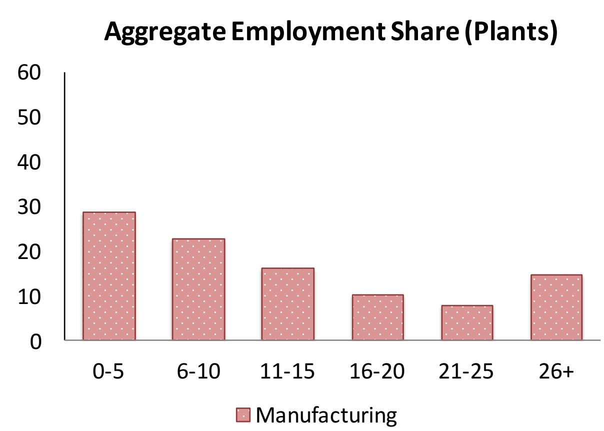
Notes: This table contains summary statistics for establishments in the Indian manufacturing sector in 2010. The data are taken from the ASI and the NSS. To calculate the number of firms, we use the sampling weights provided in the data.

Table 10: Establishment Size Distribution in India

	Plant Size				
	1-4	**5-9**	**10-19**	**20-49**	**50+**
1995	0.9163	0.0633	0.0147	0.0036	0.0021
2010	0.9297	0.0491	0.0143	0.0042	0.0027

Notes: This table presents the share of establishments for different size bins in India, for the years 1995 and 2010. Size bins are constructed based on number of employees.

Figure 8: The employment share by age of establishments in India



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

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