The Life Cycle of Plants in India and Mexico*

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Abstract

In the U.S., the average 40 year old plant employs almost eight times as many workers as the typical plant five years or younger. In contrast, surviving Indian plants exhibit little growth in terms of either employment or output. Mexico is intermediate to India and the U.S. in these respects: the average 40 year old Mexican plant employs twice as many workers as an average new plant. The divergence in plant dynamics suggests lower investments by Indian and Mexican plants in process efficiency, quality, and in accessing markets at home and abroad. In simple GE models, we find that the difference in life cycle dynamics could lower aggregate manufacturing productivity on the order of 25%.

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I. Introduction

A well-established fact in the U.S. is that new businesses tend to start small and grow substantially as they age.[1] For example, forty year old manufacturing plants are almost eight times larger than plants under the age of five in terms of employment (See Figure 1). Atkeson and Kehoe (2005) suggest that this life cycle is driven by the accumulation of plant-specific organizational capital. According to this interpretation, establishments grow with age as they invest in new technologies, develop new markets, and produce a wider array of higher quality products. Foster, Haltiwanger, and Syverson (2012) show that, even in commodity-like markets (such as white bread), establishment growth is largely driven by rising demand for the plant's products as it ages.

This paper examines the importance of the accumulation of establishment-specific intangible capital over the life cycle for understanding differences in aggregate TFP between poor and rich countries. Specifically, we focus on a comparison of the life cycle in the Indian and Mexican manufacturing sectors with the U.S. We choose India and Mexico because they have comprehensive micro-data on manufacturing establishments that allows us to measure the life cycle properly. Importantly, the data we use captures the large informal sector (as well as the formal establishments) in these countries. Most other available datasets, such as the data on Chinese manufacturing we used in Hsieh and Klenow (2009), are inadequate for measuring the life cycle as they only survey large establishments.

As preliminary evidence, consider the relationship between establishment employment and age in India and Mexico shown in Figure 1. In contrast to the U.S., in India old plants are no larger than young plants. In Mexico, 25 year old plants are twice the size of new plants, not far from the U.S. pattern for 25 year old plants. What differs between the U.S. and Mexico is that 40 year old plants in Mexico are no larger than 25 year old plants, while 40 year old U.S. plants are almost *four* times larger than their 25 year old counterparts. These facts are consistent with establishments accumulating less organizational capital in India and Mexico than in the U.S.

Why would firms in India and Mexico invest less in organizational capital? The returns to such investments might be lower in India and Mexico for a multitude of reasons. Large plants could face higher taxes or higher labor costs. Levy (2008) argues that payroll taxes in Mexico

[1] See, for example, Dunne, Roberts, and Samuelson (1989) and Davis, Haltiwanger, and Schuh (1996). Cabral and Matta (2003) provide similar evidence from Portugal.

are more stringently enforced on large plants. Bloom et. al. (2012) suggest difficulty in contract enforcement makes it costly to hire the skilled managers necessary to grow in India. Financial constraints are another possibility. Many authors have modeled the U.S. life cycle as the result of relaxing financial constraints as the establishment grows.[2] If large establishments in India and Mexico still face financial constraints, this would diminish their ability and incentive to grow. Another force might be higher transportation and trade costs that make it more difficult to reach more distant (internal or external) markets. Consistent with these stories, we find that the gap in the average revenue product of resources between high and low productivity establishments is five to six times larger in India and Mexico than in the U.S. – as if high productivity establishments face higher taxes, transportation barriers, or factor costs in India and Mexico.

To gauge the potential effect of the life cycle on aggregate productivity, we examine simple GE models based on Melitz (2003) and Atkeson and Burstein (2010). We focus on three mechanisms. First, if post-entry investment in intangible capital is lower in India and Mexico, the productivity of older plants will be correspondingly lower. Second, lower life-cycle growth reduces the competition posed by incumbents to young establishments. For this reason, slower life-cycle growth can boost the flow of entrants, increase variety, and reduce average establishment size. Third and related, a larger flow of entrants may bring in marginal entrants who are less productive than infra-marginal entrants. Based on our illustrative model calculations of moving from the U.S. life cycle to the Indian life cycle, the net effect of these three forces could plausibly account for a 25% drop in aggregate TFP.

The paper proceeds as follows. Section II describes the data. Section III presents the basic facts about the life cycle of plants in India, Mexico, and the U.S. Section IV provides suggestive evidence on forces that might be lowering the return to intangible capital in India and Mexico. Section V lays out a GE model of heterogeneous firms with life-cycle productivity to illustrate the potential consequences for aggregate productivity of differences in the life-cycle profile between India and the U.S. Section VI concludes.

[2] Cooley and Quadrini (2001), Albuquerque and Hopenhayn (2002), Cabral and Matta (2003), and Clementi and Hopenhayn (2006) are examples of models with this mechanism.

II. Data

To measure the life cycle of a cohort of establishments, we need data that is representative across the age distribution. A typical establishment-level dataset has information only on plants above a certain size threshold. This is problematic for measuring the life cycle if most new establishments are small. Our analysis focuses on the U.S., Mexico, and India as these countries have establishment level data that are representative across the full size distribution of manufacturing establishments.

For the U.S., we use data from the Manufacturing Census every five years from 1963 through 2002. The variables we use from the U.S. Census are the wage bill, number of workers, value-added, establishment identifier, book value of the capital stock, and industry (four digit SIC from 1963 to 1997 and six digit NAICS in 2002). In each year, there are slightly more than 400 industries. The U.S. Census does not provide information on the establishment's age. We impute an establishment's age based on when the establishment appeared in the Census for the first time.[3] We have data every five years starting in 1963 so we group establishments into five-year age groupings. For our analysis, we will use the Censuses from 1992, 1997, and 2002 as these are the years with the most complete age information. We also keep the administrative records in our sample. These are small plants where the Census Bureau imputes plant employment and output from payroll data (using industry-wide averages of the ratio of output and employment to the wage bill). In Hsieh and Klenow (2009) we omitted administrative records as our focus there was on the dispersion of the *ratio* of plant output to inputs. Here, our main focus is on plant employment which is not likely to be significantly biased in the administrative record establishments.

The data we use for Indian manufacturing is the Annual Survey of Industries (ASI) and the Survey of Informal Establishments of the National Sample Survey (NSS). The ASI is a census of manufacturing establishments with more than 100 employees and a random sample of formally registered establishments with less than 100 employees.[4] The NSS is a survey of

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[3] Establishments are defined by a specific physical location. The establishment identifier remains the same even when the establishment changes ownership.

[4] According to India's Factories Act of 1948, establishments with more than 20 workers (the threshold is 10 or more workers if the establishment uses electricity) are required to be formally registered. One third of the formal plants with less than 100 workers were surveyed in the ASI prior to 1994-95. The sampling probability of the smaller plants in the ASI decreased (to roughly one seventh) after 1994-95.

informal establishments conducted every five years as one of the modules of the Indian National Sample Survey. The ASI and the NSS collect data over the fiscal year (July 1 through June 30). We have the ASI for every year from 1980-81 to 2007-2008. The NSS is only available for four years: 1989-1990, 1994-1995, 1999-2000, and 2005-2006. Our analysis will focus on the years for which both the ASI and the NSS are available, and we will refer to the combined dataset as the ASI-NSS.

To make the Indian data comparable to the U.S., we restrict the analysis to sectors that are also classified as manufacturing in the U.S. data.[5] The variables we use from the ASI and the NSS are the number of paid employees, contract workers, unpaid workers, wage and non-wage compensation (for the establishments with paid employees or contract workers), total capital stock (and two of its components – machinery and equipment and value of land), value added, industry, and establishment age.[6] The NSS also separately provides the number of full-time and half-time workers. The ASI and the NSS use the same industry classification (about 400 industries each year). Establishment age is available for all years in the ASI but only available in 1989-90 and 1994-95 in the NSS. Establishment identifiers are provided in the ASI starting in 1998-99; the NSS does not have establishment identifiers. We also use information in the ASI on electricity provided by the plant's generator and purchased from the electric grid (the NSS does not have information on generators).

For Mexico, we use data from the Mexican Economic Census. The Economic Census is conducted every five years by Mexico's National Statistical Institute (known by its Spanish acronym INEGI). The Census is a complete enumeration of all fixed establishments in Mexico. The only establishments not in the Economic Census are street vendors, which are unlikely to be important in manufacturing. We have access to the micro-data of Mexican Censuses from 1998, 2003, and 2008. To make the Mexican data comparable to the U.S., we restrict our attention to establishments in the manufacturing sector.[7] The variables we use from this data are the number

[5] This primarily removes auto and bicycle repair shops that are classified as manufacturing in the Indian data. Repair shops account for roughly 20 percent of all establishments in the Indian data.

[6] The ASI does not have information on unpaid workers in 1999-2000. Unpaid workers account for 0.8 to 1.5 percent of total employment in the ASI plants in 1989-90, 1994-95, and 2005-06.

[7] There are two industries classified as manufacturing in 1998 (CMAP 311407 and 321201) but later reclassified as agriculture in 2003 and 2008. We drop these industries from the 1998 sample.

of paid employees, contract workers, unpaid workers, hours worked (for each type of worker), wage bill, labor taxes (paid to Mexico's Social Security Agency) and other non-wage compensation, total capital stock, value-added, establishment age, and industry (roughly 350 industries in manufacturing). In 2003, we also have information on machinery and equipment capital and the value of the land used by the establishment. Finally, although the Mexican data is a complete census, there are no establishment identifiers in the data and there is not enough information in the data to link establishments between census years.

Table 1 presents the number of establishments and total employment in our data.[8] We focus on establishments rather than firms. We do not have information on firms in the Indian and Mexican data. The number of workers in India and Mexico includes unpaid and contract workers. According to Table 1, most Indian manufacturing establishments are in the informal sector (i.e., in the NSS). Though informal establishments are smaller, they still account for 80 percent of total manufacturing employment in India.

III. The Life Cycle of Manufacturing Plants

This section presents the stylized facts on the life cycle of manufacturing establishments in India, Mexico, and the U.S. We control for four digit industries so all the facts we show are within-industry patterns, where we present a weighted average across all the industries using the value-added share of each industry as weights.

We begin by presenting evidence from the cross-section on the relationship between plant employment and age in the cross-section (Figure 1). The data are the 1994-95 ASI-NSS for India, 2003 Economic Census for Mexico, and the 2002 Manufacturing Census in the U.S. In the U.S. cross-section, the average plant over the age of forty is almost eight times larger than the average plant under the age of 5. In contrast, forty year old Indian plants are no larger than new plants. Mexico is an intermediate case: average employment doubles from age < 5 to age 25 but remains unchanged after age 25.

[8] We checked that the total number of workers in Indian manufacturing in Table 1 (from establishment level data) is consistent with data on manufacturing employment from India's labor force survey (Schedule 10 of the NSS). For example, the total number of manufacturing workers in the labor force survey was 35.7 million in 1999-2000 and 46 million in 2004-2005 (we computed these numbers from the NSS Schedule 10 micro-data). The corresponding numbers in Table 1 are 37 million in 1999-2000 and 45 million in 2005-2006.

The fact that older plants in India and Mexico are small may not have a large effect on aggregate outcomes if there are also fewer old plants in India and Mexico. Exit rates could be higher in India and Mexico so fewer plants survive to old age. However, Figure 2 shows that exit rates in India and Mexico are generally no higher than in the U.S. Another way to see the effect of the flat size-age profile is to look at the distribution of employment by establishment age (Figure 3). The employment distribution by establishment age is a function of the size-age relationship (Figure 1), the exit probability with age (Figure 2), and the size of each cohort at birth. If the latter two forces do not differ much between the U.S., India and Mexico, then differences in the employment distribution by age will be driven by differences in the cross-sectional relationship between employment and age. It is well known (e.g., Atkeson and Kehoe, 2005) that employment in the U.S. is concentrated in older plants. The bottom panel in Figure 3 illustrates this fact. Old establishments in the U.S. (more than 40 years old) account for almost 30 percent of total employment. Plants less than 10 years old account for slightly more than 20 percent of total employment. India and Mexico look very different in that employment is concentrated in young establishments. Establishments less than 10 years old account for 50 percent of employment in India and Mexico, while older plants (older than 40 years) account for less than 10 percent of employment.

These patterns are remarkably robust. We see a similar relationship between average size and age in all the other years of our data, when we measure plant size by value-added (instead of employment), or when we use U.S. value-added shares to aggregate the patterns within four digit industries in India and Mexico. The pattern also holds across most sectors. For example, in 17 out of the 19 two-digit industries in India, average employment is less than 20 percent higher for plants more than 40 years old compared with plants under the age of five. In the U.S., average employment is more than seven times higher in older plants (more than 40 years old) in 17 out of 19 two-digit industries.

Although suggestive, the relationship between plant employment and age in the cross-section conflates size differences between cohorts at birth and employment growth of a cohort over its life cycle. Ideally we want to measure the growth of a cohort of plants as it ages, rather than make inferences about the life cycle from cross-sectional evidence. We have establishment data from 1963 to 2002 for the U.S. so we can follow a cohort over 40 years in the U.S. In India, we have data on establishment age only for 1989-90 and 1994-95 so we can only follow each cohort over these five years only. In Mexico, we have data for 1998, 2003, and 2008 so we can follow cohorts for up to ten years.

Given these data limitations, we measure the "life cycle" in the following manner. In India, we compare the average size of establishments of a given cohort in 1989-90 with the size of the same cohort five years later (in 1994-95). We do this for all the cohorts grouped into five-year age bins. If we assume that every cohort experiences the same life-cycle growth, we can impute the life cycle from the growth in average size of the different cohorts from 1989-90 to 1994-95. For comparability with the Indian data, we follow the same procedure for Mexico and the U.S. For Mexico, we impute the life cycle from the employment growth of each cohort from 1998 to 2003 and for the U.S. from the employment growth from 1992 to 1997.[9]

Figure 4 presents the life cycle of plant employment calculated in this manner. In India the over-time evidence suggests, by age 35, average plant employment falls to *one-fourth* of its level at birth. The evidence from cross-sectional data indicates a smaller decline in India. For the U.S., the over time evidence suggests that average plant size increases by a factor of ten from birth to age 35; the cross-sectional evidence suggests that average plant size experiences less than an eight-fold increase. In Mexico, both the over-time and the cross-sectional evidence suggest a similar increase in plant size with age.

We emphasize again that imputing the life cycle from two cross-sections is valid only if all cohorts experience the same life-cycle growth. We can check this assumption in the U.S. and Mexico. In the U.S., when we follow the cohort of new establishments in 1967 (recalling that we have to impute age based on when the establishment appears in the census for the first time) until 1997, we get estimates of the life cycle that are similar to that imputed from employment growth from 1992 to 1997. In Mexico, we can also impute the life cycle using the employment change from 2003 to 2008. Again, we get estimates of the life cycle similar to that shown in Figure 4.

Growth in average employment of a cohort can be driven by growth of survivors and by the exit of small establishments. Several authors, including Ericson and Pakes (1995), Hopenhayn (1992), Jovanovic (1982), and Luttmer (2007), model the evolution of the U.S. life cycle via the selection mechanism rather than survivor growth. We now probe for evidence of

[9] We did not use the employment growth from 1997 to 2002 in the U.S. because the U.S. industry classification changed from 1997 to 2002.

the importance of the selection effect in explaining the difference in the life cycle between the U.S. and India. Figure 5 presents the growth in average employment of all establishments (as in Figure 4) and the growth of *surviving* establishments in India and the U.S. The U.S. data is from the Manufacturing Censuses of 1992 and 1997 and the Indian data is from the ASI (the survey of formal establishments) from 1998-99 to 2003-04 (we have establishment identifiers in the ASI starting in 1998-89). The ASI is not representative of all Indian manufacturing as it only includes formal establishments, but we think the ASI evidence is still useful. In the U.S. and in formal Indian plants, survivor growth is lower than overall growth, suggesting that exit in the two countries is negatively correlated with size. The contribution of selection to the growth in the average size of a cohort is about the same in formal Indian plants as in U.S. manufacturing.

We reiterate that the Figure 5 evidence is not conclusive as we do not have evidence from informal Indian plants. However, it suggests that the flatter life cycle in India is *not* because larger plants are more likely to exit (and smaller plants less likely to exit) than in the U.S. Instead, what appears to differ between India and the U.S. is the growth of incumbents. In the U.S, surviving establishments experience substantial growth. In India, incumbent firms become *smaller* with age. This fact points to the anemic growth of incumbents in India as a force for the flat life cycle in Indian plants.

IV. Why Don't Plants Grow in India and Mexico?

In this section, we impose more structure on the data to "explain" the low employment growth of Indian and Mexican plants with age. First, we show that low employment growth can largely be attributed to low productivity growth with age. Second, we show that the return on investments to boost plant productivity may be lower in India and Mexico, and provide suggestive evidence on forces that might be behind the lower returns.

Productivity over the life cycle

Consider a closed economy version of Melitz (2003). Suppose that aggregate output at time *t* is given by a CES aggregate of the output of individual establishments:

(1.1) $$Y = \left[\sum_{a} \sum_{i=1}^{N_a} Y_{a,i}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

Here i indexes the establishment, a refers to the establishment's age, N_a the number of establishments of age a (we suppress the subscripts for sector and time when possible), $Y_{a,i}$ is the value added of plant i of age a, and $\sigma > 1$ is the elasticity of substitution between varieties.

Each plant is a monopolistic competitor choosing its labor and capital inputs (and therefore its output and price) to maximize current profits

(1.2) $$\pi_{a,i} = (1-\tau_{Y_{a,i}})P_{a,i}Y_{a,i} - w(1+\tau_{L_{a,i}})L_{a,i} - (1+\tau_{K_{a,i}})RK_{a,i} ,$$

where $P_{a,i}$ is the plant-specific output price, $L_{a,i}$ is the plant's labor input, $K_{a,i}$ is the plant's capital stock, and R is the common undistorted rental cost of capital. Here $\tau_{Y_{a,i}}$ denotes an establishment-specific revenue distortion, $\tau_{K_{a,i}}$ a capital distortion, and $\tau_{L_{a,i}}$ a labor distortion. Such wedges might arise for any number of reasons, such as taxes, markups, adjustment costs, transportation costs, size restrictions, labor regulations, and financial frictions.[10]

Suppose, further, that plant output is given by a Cobb-Douglas production function

(1.3) $$Y_{a,i} = A_{a,i} K_{a,i}^{\alpha} L_{a,i}^{1-\alpha} ,$$

where $A_{a,i}$ is plant-specific productivity. It is process efficiency here for concreteness, but in terms of the data we have it will be observationally equivalent to plant-specific quality or variety under certain assumptions (see the appendix in Hsieh and Klenow, 2009).

The equilibrium revenue and employment of the plant are then proportional to

(1.4) $$P_{a,i}Y_{a,i} \propto \left(\frac{A_{a,i}}{\tau_{a,i}} \right)^{\sigma-1}$$

[10] For a few recent examples see Restuccia and Rogerson (2008), Guner, Ventura and Xu (2008), Midrigan and Xu (2010), Buera, Kaboski and Shin (2011), Peters (2011), and Moll (2012).

(1.5)
$$L_{a,i} \propto \frac{A_{a,i}^{\sigma-1}}{\tau_{a,i}^{\sigma}}$$

where $\tau_{a,i} \propto \frac{\left(1+\tau_{K_{a,i}}\right)^{\alpha}\left(1+\tau_{L_{a,i}}\right)^{1-\alpha}}{1-\tau_{Y_{a,i}}} \propto \left(\frac{P_{a,i}Y_{a,i}}{K_{a,i}}\right)^{\alpha}\left(\frac{P_{a,i}Y_{a,i}}{L_{a,i}}\right)^{1-\alpha}$ is a weighted average of the average revenue product of capital and labor. See Hsieh and Klenow (2009) for additional details. We are building on the work of Foster, Haltiwanger and Syverson (2008), who distinguish between "revenue" TFP (TFPR, or $\tau_{a,i}$ here) and "quantity" TFP (TFPQ, or $A_{a,i}$ here).

As shown in (1.4) and (1.5), a plant's revenue and employment is increasing in its productivity A and decreasing in its average product τ. More productive plants have lower costs and therefore charge lower prices and reap more revenue (given $\sigma > 1$), for a given τ. Plants with a higher τ charge higher prices and earn less revenue, for a given level of productivity. More to the point of our analysis here, the *growth* of plant revenue and employment with age (in the cross-section) then depends on the growth of plant productivity with age and the extent to which the value of plant average product changes with age.

We need data on PY, K, L, and α to measure plant productivity and average product. We measure PY as plant value-added, K as the book-value of the capital stock, and $1-\alpha$ as the wage-bill share of the sector (as measured in the U.S. data). In Hsieh and Klenow (2009), we measure L as the plant's wage-bill. We do not do that here because a large number of establishments in India and Mexico do not have paid workers. In the U.S., we measure plant employment as the total number of workers. In India, we measure employment in the ASI plants as the number of workers and in the NSS plants as the number of full-time equivalent workers (we assume a part-time worker is equivalent to half a full-time worker). In Mexico, we measure employment as the total number of hours worked.

Using this data, Figure 6 plots the evolution of plant productivity over the life cycle.[11] For Mexico and the U.S. the life cycle of plant productivity roughly tracks the life cycle of plant size. For India, it looks quite different. Plant productivity in India increases with age, roughly doubling by age 35, while employment falls with age (Figure 4). From equation (1.5), the average product in India must be rising with age to explain these two facts. Figure 7 plots the

[11] This is actually life cycle productivity growth *relative* to the productivity growth of entering cohorts, as the productivity of the youngest cohort is normalized to one in each year.

average product (of capital and labor) over the life cycle. In India, the average product of capital and labor is eight times higher in 35 year old Indian plants compared to new plants. Older Indian establishments are smaller than they would be in an economy where marginal products were equalized across plants by age. In Mexico and the U.S., the average product of 35 year old plants is roughly the same as that of new plants. Because of this, employment grows with age in Mexico and the U.S. at the same rate that productivity grows with age.

We summarize the key findings. From birth to age 35, plant employment increases by a factor of ten in the U.S., a factor of two in Mexico, and *declines* in India. In turn, these differences can be traced to the fact that plant productivity increases by a factor of eight in the U.S. by age 35, vs. only by a factor of two in India and Mexico. Why do Indian and Mexican establishments experience so little productivity growth over their life cycle? This is the question we turn to next.

Returns to Investment in Plant Productivity:

Consider again the closed-economy Melitz model of the previous section, only now with endogenous productivity growth. Plants are born with an exogenously given level of productivity. Incumbents decide how much to invest to boost future productivity. For simplicity, assume no uncertainty and that plants live for two periods. (The next section adds uncertainty and many periods.) The marginal increase in profit from a proportional increase in productivity is

$$MB_i \propto \left(\frac{A_i}{\tau_i}\right)^{\sigma-1}.$$

The return from investment in organizational capital is increasing in the ratio of productivity to τ. Thus the elasticity of τ with respect to productivity will matter. To fix ideas, suppose we parameterize the relationship as $\tau_i \propto A_i^{\beta}$. The return from a proportional increase in productivity is then $MB_i \propto A_i^{(1-\beta)(\sigma-1)}$, which is decreasing in β (the elasticity of τ with respect to productivity) for a given level of productivity.

Figure 8 plots τ vs. productivity of different age plants in the cross-section. τ rises much more steeply with productivity in India and Mexico. In India and Mexico, a doubling in establishment productivity is associated with a 50-60 percent increase in the average product of factor inputs. In the U.S. the same two-fold productivity gap is associated with a 10 percent gap in average products. This pattern could reflect larger markups in high productivity plants, but this interpretation would imply that Indian and Mexican plants have *more* incentive to grow. We instead pursue the possibility that more productive plants face higher marginal input costs in India and Mexico.

We start by looking at the convexity of the cost of labor. There is a large literature on contractual frictions that increase the cost of wage labor relative to family labor. Since the marginal worker for a large plant is likely to be a wage worker, these frictions increase the marginal cost of labor for large plants relative to smaller plants. Labor regulations and taxes that apply to large firms (or that small firms find easy to evade) could also raise the cost of labor for large firms. Indian labor regulations emphasized by Besley and Burgess (2004) are a prime example. In Mexico, Levy (2008) argues that payroll taxes (roughly 32 percent of the wage bill) are more stringently enforced on large firms, as are other taxes (Anton, Hernandez and Levy, 2012). Bloom et. al. (2012) argue that delegation costs raise the costs of managers in India. In an appendix, we sketch a model where managerial inputs are important for large plants but less important for smaller plants. A higher cost of managers in India and Mexico would make the effective cost of labor more convex than in the US.

If labor costs are more convex with size in India and Mexico, we expect to see more firms choosing to remain small and informal to avoid higher labor costs associated with size. Table 2 presents the facts on the prevalence of informal and family-owned establishments in the Indian and Mexican manufacturing sector. Here, we define family establishments in India as those that *only* employ unpaid workers and informal establishments as those not registered in India. For Mexico we define informal establishments as those not registered with Mexico's Social Security Agency (IMSS). Establishments that *only* employ unpaid workers account for 72 percent of employment in India in 1989-90. The employment share of family owned firms in Mexico is lower. But note that informality has increased in Mexico. For example, the employment share of family plants increased from 10 in 1998 to almost 30 percent by 2008.

The gap in average wages between large and small plants (Figure 9) provides another piece of evidence. For the U.S., we see the well known fact that average wages are higher in larger establishments. Average wages in large plants are also higher in India and Mexico, but the gap in average wages between large and small establishments is almost twice that observed in the U.S. This evidence suggests that larger establishments may pay higher efficiency wages due to monitoring costs or that the cost of skilled managers is higher in India and Mexico.

In the U.S. there is some evidence that larger establishments have better access to capital, and many papers have modeled the U.S. life cycle as driven by the endogenous relaxation of financial constraints as the establishment grows. If financial markets do not work as well in India and Mexico, this process could be attenuated in India and Mexico. Frictions in land markets may also prevent high productivity firms from physically expanding as much as they would like. Figure 10 plots the average product of land (top panel) and machinery and equipment (bottom panel) against plant employment in India and Mexico. There is clear evidence that the average product of land is rising with establishment size in India. This could be evidence of technological differences (e.g., larger establishments are naturally less land intensive), but it can also be evidence that frictions to land reallocation raise the marginal cost of land faced by high productivity firms. In contrast, the Mexican data speak less clearly on the importance of land market frictions. Turning to the cost of machinery and equipment, one might expect larger establishments to be more capital intensive, either because they use more capital-intensive technologies or because they face a lower cost of capital. This, however, does not appear to be the case. The average product of machinery and equipment is increasing with size in Mexico. In India the average product of machinery and equipment is only marginally higher for larger plants.

The cost of intermediate inputs can also be more convex in India and Mexico. Consider electricity. The survey of formal establishments in India (the ASI) explicitly asks whether an establishment has an electricity generator and the quantity of electricity produced from the generator.[12] In 1994-95, for example, about one-third of formal Indian establishments report owning a generator. Figure 10 plots the establishment's electricity purchased from the grid as a percent of its total consumption of electricity as a function of the establishment's employment. We present this information separately for all ASI plants and for ASI plants that report owning a generator. Looking at all plants, small plants purchase virtually all their power from the grid, while the largest plants rely on generators for about 30 percent of their electricity use. When the sample is restricted to establishments that operate a generator, small plants obtain roughly 20 percent of their electricity from their generator. Importantly, this share rises to almost 40 percent

[12] There is no equivalent information in the Indian NSS or the Mexican Census.

for large plants. This evidence suggests that the supply of power from the electric grid is limited and that the marginal cost of electricity for larger plants is more likely to be the higher unit cost of generator supplied electricity.

The returns to innovation can also be more concave in India and Mexico than in the US. Income or sales taxes that apply to large establishments are an obvious candidate explanation. If corruption has a larger effect on large establishments, this would also have the same effect.[13] Another explanation is that the cost of expanding to new markets may be higher in India and Mexico. Holmes and Stevens (2012) show that in the U.S., larger establishments sell to more distant domestic markets. In an appendix, we sketch a model where there is a continuum of markets that differ in distance (from the firms) and transportation costs are higher the more distant the market. In this framework, higher shipping costs lowers the number of markets a firm with a given level of productivity sells to. In turn, this lowers the returns from investing in higher productivity.

The examples we discussed in this section are meant to be illustrative. Surely other mechanisms play a role as well. Identifying which mechanisms are important is an important agenda for future work, but we will not attempt to do that systematically here. Instead, we merely want to stress the implication of the higher elasticity of τ with productivity, whatever the source, for the return from investing in projects that boost firm productivity. Here, the cross-sectional relationship between τ and productivity suggests that the returns to investments that boost firm productivity are lower in Mexico and India relative to the U.S. In the next section, we will turn to an assessment of the implications for aggregate TFP.

V. Impact of the Life Cycle on Aggregate Productivity

We now illustrate the potential impact of U.S. vs. Indian life cycle productivity growth on the level of aggregate productivity.[14] We do this for a sequence of simple GE models built around monopolistic competitors with life cycle productivity. In addition to Melitz (2003), we

[13] La Porta and Shleifer (2008) document that larger formal establishments pay more bribes (as a share of total revenues).

[14] As Mexico is an intermediate case in most patterns (life cycle growth, size distribution, etc.), we set it aside for now in this section.

follow Atkeson and Burstein (2010) in many of our modeling choices. For all of the models we assume:

(a) a closed economy
(b) no aggregate uncertainty
(c) additively time-separable isoelastic preferences over per capita consumption
(d) constant exogenous growth in mean entrant productivity A
(e) labor as the sole input (including for entry and innovation when endogenous)
(f) fixed aggregate supply of labor (equal to the population)
(g) exit rates as a fixed function of a plant's age (and A if it differs within cohorts)
(h) τ as a fixed function of a plant's age (and A if it differs within cohorts)

These assumptions imply two convenient properties about the resulting equilibria:

(i) a stationary distribution of plant size in terms of labor
(j) a balanced growth path for aggregate TFP, the wage, and per capita output/consumption and (related) a fixed real interest rate

See Luttmer (2010) as well as Atkeson and Burstein (2010).

For each model, aggregate TFP is the same as output per capita, as there is no capital. Aggregate TFP can therefore be expressed as

$$TFP = \frac{Y}{L} = \left[\sum_{a} \sum_{i=1}^{N_a} \left(A_{a,i} \cdot \frac{\bar{\tau}}{\tau_{a,i}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}} \frac{L_Y}{L} \tag{1.6}$$

where $Y_{a,i} = A_{a,i} L_{a,i}$ and $\tau_{a,i} \equiv \frac{P_{a,i} Y_{a,i}}{L_{a,i}} = P_{a,i} A_{a,i}$. As these models do not have capital, we assume a single revenue distortion hitting each plant.[15]

In (1.6), L_Y / L is the fraction of the labor force working to produce current output. The total workforce is fixed at $L = L_Y + L_R$ each period. L_Y itself is the sum of production labor across all plants, and L_R is sum of people working in the research sector to improve process efficiency for incumbents and/or come up with new varieties for entrants.

We start by assuming the flow of entrants is fixed over time, and requires no labor. We first entertain a version in which *A* varies only by age. All entrants have the same *A*, and it grows exogenously with age. Exit rates depend on age only. And all firms have the same τ. In this case we simply get

(1.7)
$$TFP = \left[\sum_a N_a A_a^{\sigma-1} \right]^{\frac{1}{\sigma-1}}.$$

Implicit in (1.7) is allocation of labor to efficiently exploit variation in *A* across cohorts. We calculate aggregate TFP in this way with U.S. *A* by age and, separately, with *Indian A* by age. We normalize the mass of entrants to $N_1 = 1$, and keep the exit rates by age at U.S. levels displayed in Figure 8.[16] Table 3 lists the parameter values chosen for this model and subsequent models.

The first column of Table 4 reports that, in this simplest GE model, going from U.S. to Indian life cycle *A* growth lowers average TFP by 24%. To put this into perspective, aggregate TFP in Indian manufacturing is about 62% below that in the U.S. (see Hsieh and Klenow, 2009). So slower life cycle TFPQ growth might account for about one-fourth of the aggregate TFP difference (ln(0.76)/ln(0.38) ≈ 0.28). But note that this assumes no response of entry to life cycle growth.

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[15] In terms of the earlier notation, $\tau_{a,i} = \frac{1}{1-\tau_{Y_{a,i}}}$. And $\bar{\tau} = \frac{\sigma}{\sigma-1} \frac{w}{\sum_a \sum_{i=1}^{N_a} \frac{P_{a,i} Y_{a,i}}{PY} \frac{1}{\tau_{a,i}}}$.

[16] For the age 35+ cohorts, we estimate the exit rate and the growth rate of *A* by comparing the 35+ group to the 30+ group. We assume all plants die by age 100 years for computational convenience.

In the data, average plant size is smaller in India (and Mexico) than in the U.S. Figure 12 plots the plant size distribution in the three countries to illustrate this fact. Thus entry is higher in India and Mexico than the U.S. Might this be due, in part, to the different life cycle growth of Indian and Mexican plants? In a Melitz-style model with incumbent innovation, Atkeson and Burstein (2010) show that lower *A* growth of incumbents can encourage entry. When entrants face less competition from efficient incumbents, they enjoy higher discounted profits *ceteris paribus*. Entrants will become incumbents, of course, but they discount their lower future profits at the time of entry. The higher discounted profits increase entry and lower average plant size to maintain the free entry condition (zero discounted profits) in equilibrium. Atkeson and Burstein (2010) find that, in response to higher trade barriers, the benefits of higher entry can largely offset the costs of lower average *A*.[17]

The second column in Table 4 shows what happens when we allow for endogenous entry when moving from U.S. to Indian life cycle growth. Average *A* falls by a similar amount, 25%. Entry rises 17%. The net effect on aggregate TFP is still negative at around -19%. Even with our low substitutability ($\sigma = 3$) and therefore strong love of variety, 17% more variety lifts aggregate TFP only about 8%. And the additional entry diverts some labor from goods production, lowering the share of people producing current output by over 4%.

Recall that *A* growth is not the whole story behind life cycle employment growth in India vs. the U.S. τ increases with age in India, whereas it falls with age in the U.S. We next add age-specific tax rates to the model – a reduced form for not just tax rates but size restrictions, labor regulations, financing costs, and so on. The penultimate column of Table 4 shows that this distortion has a modest effect on aggregate TFP with fixed entry. Whereas moving from U.S. to Indian *A* by age lowers aggregate TFP by 24.4%, moving from U.S. to Indian τ by age at the same time lowers productivity 25.7%. The final column of Table 4 adds back free entry to this scenario. The steeper τ by age in India galvanizes entry (now up 49%, vs. 17% with only *A* by age). Discounted profits rise even more if older plants are restrained (in terms of τ) as well as growing slowly in terms of *A*. Even though 11% of the labor force shifts from producing goods to producing new varieties, the result is a more modest drop in aggregate TFP of 9% (vs. 19%

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[17] One can re-write (1.7) as $TFP = N^{\frac{1}{\sigma-1}}\left[\sum_a \frac{N_a}{N} A_a^{\sigma-1}\right]^{\frac{1}{\sigma-1}}$, the product of a variety term and an average *A* term.

with free entry and only A changing with age). Fattal Jaef (2012) obtained a similar variety offset when considering the costs of rising τ with age in a closely related model.

Two comments about the variety offset deserve mention here. First, the model assumes a linear entry technology. Doubling entry of the same quality (A) requires twice as much entry labor. If there are instead diminishing returns of some form, then variety might not respond as flexibly to life cycle A and/or τ. We will provide a specific example below. Second, the model assumes a final goods sector which buys every variety. Yet many small manufacturers in India – for example those making food and furniture in rural areas – may sell directly to only a small set of local consumers. Li (2011) provides evidence that households in India do not consume all varieties of food, though richer and urban families consume more varieties than poorer and rural households do. Arkolakis (2010) argues that a variety of trade evidence supports convex costs of accessing buyers within countries; see also the model in our Appendix.

Another missing ingredient from the Table 4 models is A dispersion within age cohorts. Now suppose, as in Melitz (2003), entrants are homogenous *ex ante* (drawing from the same distribution of initial A) and heterogeneous *ex post* (based on realizations of the A draws). We start with fixed entry. In this environment, the effects of going from U.S. to Indian life cycle A are similar to those in the first two columns of Table 4, which feature no τ dispersion and τ dispersion only by age, respectively. So A dispersion within cohorts, by itself, does not amplify or diminish the losses from slow life cycle A growth. The same is true if we allow τ to differ by A within age groups in a common way across countries. In the U.S. the elasticity of τ with respect to A is 0.13. Perhaps not surprisingly, this too has little effect on the productivity drop when going from U.S. to Indian life cycle A and τ.

In Table 5 we consider richer models featuring A and τ dispersion within cohorts, and a different slope of τ with respect to A between the U.S. baseline and the Indian alternative. In India, the slope of τ with respect to A is much steeper at 0.56.[18] Again, this might reflect some combination of size restrictions, tax rates, labor regulations, markups and so on. The first column shows that going from U.S. to Indian A by age *and* τ by both age and A results in 54.5% lower aggregate TFP when entry is fixed. This loss is much higher because of the static

[18] If τ increases too rapidly with A, then plant employment is actually decreasing in plant A. The cutoff elasticity is $(\sigma-1)/\sigma$, which is 2/3 when $\sigma=3$. Given the elasticity is 0.56 in India, we do observe rising employment with respect to A in India.

misallocation created by greater τ dispersion across plants with different A levels in India.[19] In the second column of Table 5 we allow for endogenous entry. Entry surges 49%. As a result the share of the workforce producing output falls 12%. The net effect is a similar drop in aggregate TFP of 51%. Thus, incorporating the steeper slope of τ with respect to A in India results in a weaker variety offset.

So far we have set the initial entrant A distribution to match the U.S. data. But in the data A is more dispersed for young plants in India than in the U.S. The standard deviation of log A is 1.25 in India vs. 1.01 in the U.S. for plants age 0-4.[20] In Mexico, the standard deviation log A is 1.46. Greater entrant A dispersion in India could be a byproduct of greater entry in India. To illustrate this possibility, suppose there is a fixed mass of potential entrants as in Chaney (2008). These potential entrants observe their A *ex ante.* Instead of a free entry condition, wherein expected profits are zero for all entrants, there is a marginal A entrant with zero discounted profits. All those with initial A above the zero-profit threshold enter and earn positive discounted profits. The penultimate column of Table 5 considers this case. We calibrated the mass of potential entrants so that we can match the A dispersion in India when we go from U.S. A and τ to Indian A and τ. As shown, we obtain a modestly larger drop in aggregate TFP of -55% (vs. 51% in the previous column). There are two offsetting forces here. Average A of entrants *falls* by 49%, whereas it was previously fixed. This helps drag down the average A of all plants by 65%. But variety is up 62%. Entry labor is now quite small to explain why the low A marginal entrant has zero profits, so the surge of entry in the "Indian" counterfactual does not require much labor.

The final column in Table 5 endogenizes incumbent A growth *a la* Atkeson and Burstein (2010).[21] Incumbents choose the probability q of taking a step up vs. down in proportional A terms. (We use Atkeson and Burstein's step size, chosen to match the 25% standard deviation of employment growth of large plants in the U.S.) The marginal cost of this investment for a plant is

[19] Although similar to the 40-60% figure in our earlier (2009) paper, they are not exactly comparable. There we considered going from Indian to U.S. τ dispersion, including τ dispersion that did not relate to either A or age. And we held fixed the distribution of A in our calculation.

[20] The standard deviation of log A of new (age < 5) plants in Mexico is 1.46.

[21] For simplicity we revert to zero expected profits for all entrants.

$$MC\left(A_{a,i}, q_{a,i}\right) = h\, A_{a,i}^{\frac{1}{\sigma-1}} exp\left(b \cdot q_{a,i}\right) \quad (1.8)$$

In this formulation, it is exponentially more costly for higher A plants to boost their A by a given percentage. Atkeson and Burstein make this assumption to satisfy Gibrat's Law (a plant's growth rate is uncorrelated with its initial size) for large plants. The convex cost of process innovation is counterbalanced by the greater incentive of big plants to innovate, as gains are proportional to a plant's size. We choose the levels of h and b to fit A by age in the U.S. We then gauge the effect of moving from the joint distribution of τ with A and age in the U.S. to the distribution of τ with A and age in India. Figure 8 plots the relationship between average τ and A. The steeper slope of τ with respect to A in India discourages incumbent innovation in the same way that trade barriers do in Atkeson and Burstein's analysis. The result is 55% lower A of the average plant.[22] As entrants have less competition from incumbents, entry rises 74%. The share of the population working falls 9%, less than the 12% under exogenous innovation because some labor is freed up from doing innovation for incumbents. Aggregate TFP falls 47%. Again, less than the 51% when life cycle growth is exogenous because R&D labor is saved when innovation is discouraged.

VI. Conclusion

In Hsieh and Klenow (2009), we provide suggestive evidence that holding the distribution of plant productivity fixed, resource misallocation between existing plants can account about 30% of the gaps in aggregate manufacturing TFP. One way to interpret this evidence is that although differences in the extent of resource misallocation are important, the differences in plant productivity (which we held fixed) is really what accounts for most of the gaps in aggregate TFP between poor and rich countries.

In this paper, we take up the question we left unanswered in our previous work. Why is average plant productivity lower in poor countries? We argue that a certain type of misallocation

[22] The "τ explanation" may be sensitive to the exact source of rising τ with respect to A in India. We have modeled it as rising tax rates. Rising markups, for example, might have ambiguous incentives for incumbent innovation.

– specifically misallocation that harms large establishments – can discourage investments that raise plant productivity and thus lower the productivity of the average plant in poor countries. A key fact consistent with this interpretation is that manufacturing plants in the US grow with age while manufacturing plants in Mexico and India exhibit little growth in terms of employment or output. We use some simple GE models to show that lower life-cycle growth in Mexico and India can have important effects on aggregate TFP. Moving from the U.S. life cycle to the Indian life cycle could plausibly produce a 25% drop in aggregate TFP.

An important question is what exactly are the barriers facing larger plants in India and Mexico. We provide suggestive evidence on a number of barriers facing larger plants in India and Mexico *vis a vis* the U.S., such as bigger contractual frictions in hiring non-family labor, higher tax enforcement on larger firms, financial frictions, difficulty in buying land or obtaining skilled managers, and costs of shipping to distant markets. We hope to investigate the driving forces more systematically in future work.

Table 1: Data

Indian Annual Survey of Industries and National Sample Survey

	# Establishments (Raw Data)		# Establishments (w/ Sampling Weights)		# Workers (w/ Sampling Weights)	
	ASI	NSS	ASI	NSS	ASI	NSS
1989-90	45	97	90	13,760	6,902	25,764
1994-95	52	159	107	12,296	7,689	20,570
1999-00	24	55	117	14,032	7,906	29,109
2005-06	42	83	125	17,054	8,810	36,408

Mexican Economic Census

	# Establishments	# Workers
1998	344	4,226
2003	329	4,199
2008	437	4,661

United States Manufacturing Census

	# Establishments	# Workers
1992	371	16,949
1997	363	16,805
2002	351	14,664

Note: Units in thousands

Table 2: Informal Workers and Establishments in India and Mexico

	Unpaid Workers		Informal Establishments	
	% Workers	% Establishments	% Workers	% Establishments
India				
1989-90	71.9	94.1	78.9	99.4
2005-06	62.0	90.9	80.5	99.3
Mexico				
1998	10.2	55.0	14.8	75.6
2008	29.7	60.0	30.4	87.1

Note: % workers is percent of unpaid workers or workers in informal establishments as share of total workers. Informal establishments defined as establishments not formally registered (in India) or not registered with Social Security Agency (in Mexico). Sources: ASI-NSS (India) and Economic Census (Mexico).

Table 3: Parameter Values

Parameter	Definition	Value or Target
σ	Elasticity of substitution between varieties	3 for all models
f_e	Entry costs (in terms of labor)	Average workers per plant in the U.S.
g_e	Growth of mean of entrant ln(A)	2.1% per year for all models (U.S. average TFP growth)
$A_{a,i}$	Productivity across and within age groups	Matches growth for each 5 year age cohort in the U.S. or India
$\delta_{a,i}$	Exit by age, productivity	Matches average rate for each 5 year age cohort in the U.S.; slope with respect to ln(A) in the U.S. (-0.0225)
$\tau_{a,i}$	Tax rate on revenue by age, productivity	Matches average ln(τ) in 5 year cohorts in the U.S. or India; slope of ln(τ) wrt ln(A) in the U.S. (0.13) or India (0.56)
σ_e	S.D. of entrant ln(A)	1.01 (when not zero) to match U.S. entrant A dispersion
h	Level parameter in the R&D cost function	Set with b to match average U.S. A growth from age 0 to 30
b	Convexity parameter in the R&D cost function	Set to 100 to roughly match average Indian A growth by age
γ	Coefficient of relative risk aversion	2 for all models
ρ	Discount rate	Always 0.8% per year to arrive at a real interest rate of 5%

Table 4: % changes when going from U.S. to Indian Life Cycle

Common *A* and *τ* within cohorts

	A **by Age**	**+ Free Entry**	***A*, *τ*** **by Age**	**+ Free Entry**
Weighted Average *A*	-24.4%	-25.0%	-25.7%	-25.4%
Entry	0%	+17.2	0%	+48.9%
(Production Workers)/Workforce	0%	-4.6%	0%	-11.2%
Aggregate TFP	-24.4%	-18.8%	-25.7%	-9.0%
Model Ingredients				
A variation by:	**Age**	**Age**	**Age**	**Age**
τ variation by:	None	None	**Age**	**Age**
Free Entry	No	**Yes**	No	**Yes**
Incumbent Innovation	No	No	No	No

Source: Author calculations using code adapted from Atkeson and Burstein (2010). In all cases exit varies by age as in the U.S.

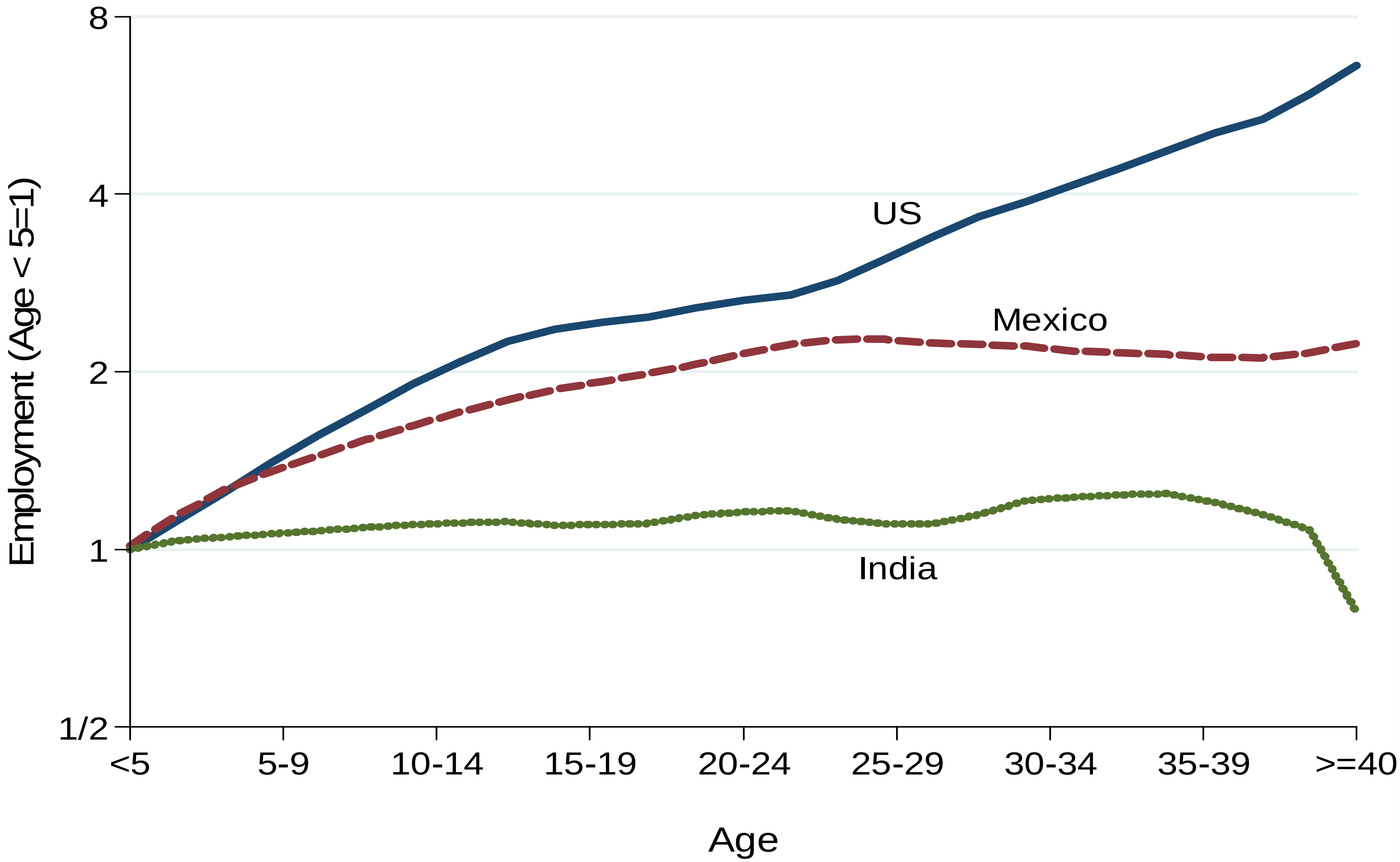
Table 5: % changes when going from U.S. to Indian Life Cycle

Dispersion in *A* and *τ* within cohorts

	Fixed Entry	Free Entry	Endogenous Entrant Quality	Incumbent Innovation
Weighted Average *A*	-54.5%	-54.5%	-64.6%	-55.7%
Entry	0%	+49.3%	+62.1%	+73.9%
(Production Workers)/Workforce	0%	-12.3%	-0.0%	-9.4%
Aggregate TFP	-54.5%	-51.2%	-54.9%	-47.1%
<u>Model Ingredients</u>				
A, τ variation by:	Age, Within	Age, Within	Age, Within	Age, Within
Free Entry	No	**Yes**	**Yes**	**Yes**
Endogenous Entrant Quality	No	No	**Yes**	No
Incumbent Innovation	No	No	No	**Yes**

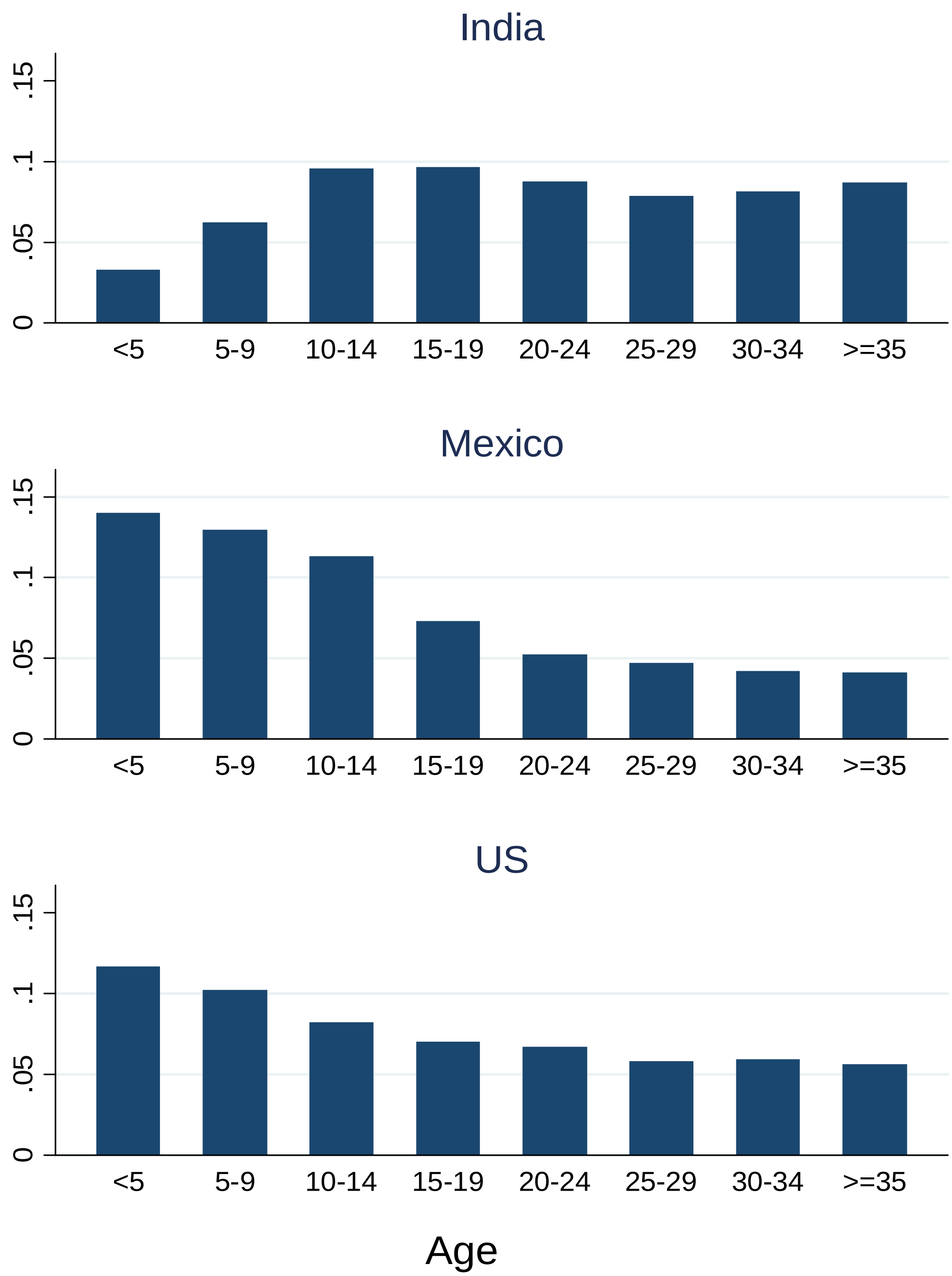
Source: Author calculations using code adapted from Atkeson and Burstein (2010). Exit varies by both age and *A* as in the U.S.

Figure 1: Plant Employment by Age in the Cross-Section



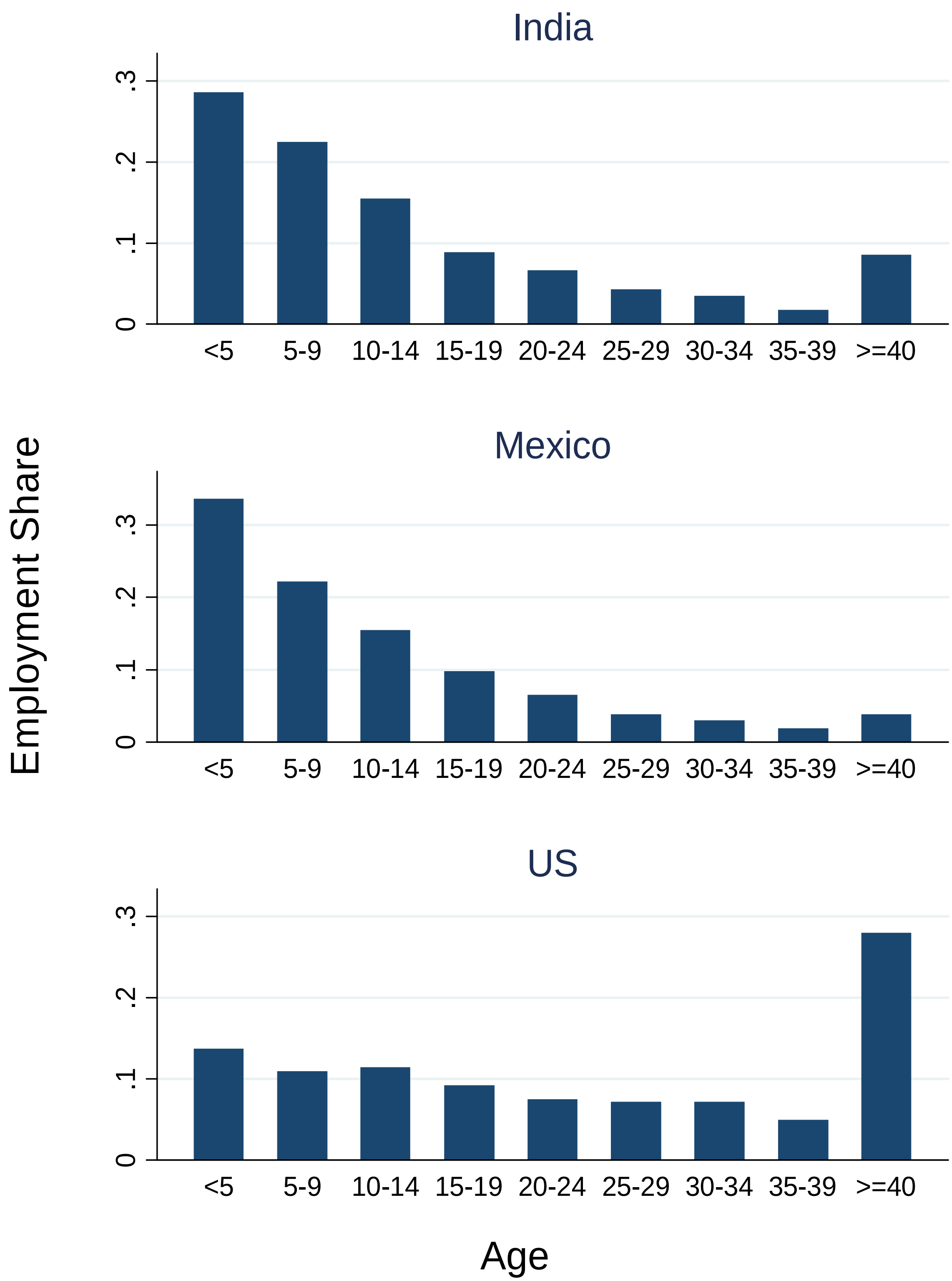
Sources: 1994-95 ASI-NSS (India), 2003 Economic Census (Mexico), and 2002 Manufacturing Census (US).

Figure 2: Exit Rate by Age



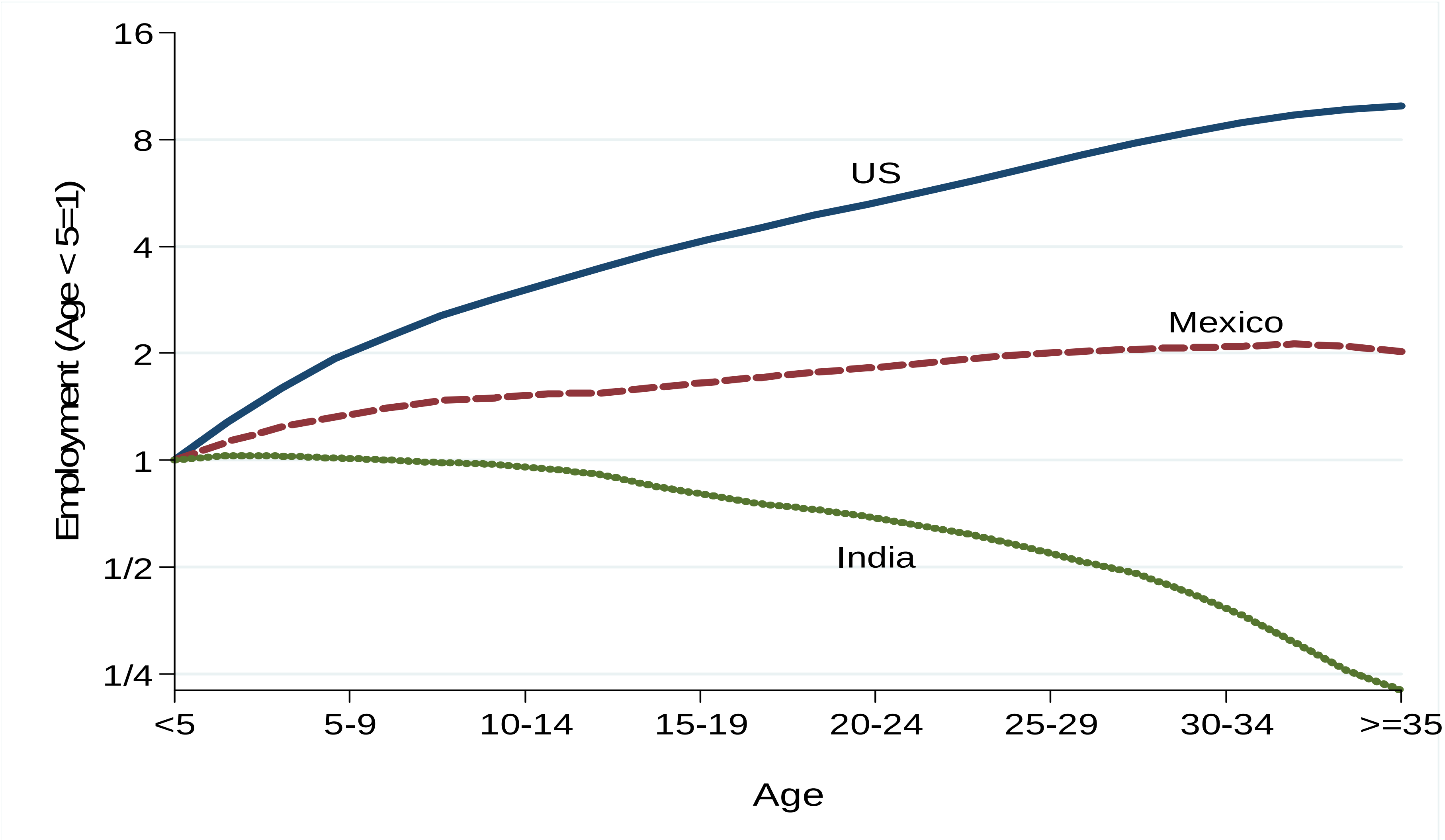
Notes: Exit Rate calculated from 1992 to 1997 (US Manufacturing Census), 1989-90 to 1994-95 (India ASI-NSS), and 1998 to 2003 (Mexican Manufacturing Census).

Figure 3: Employment Share by Age



Sources: 1994-95 ASI-NSS (India), 2003 Economic Census (Mexico), and 2002 Manufacturing Census (US).

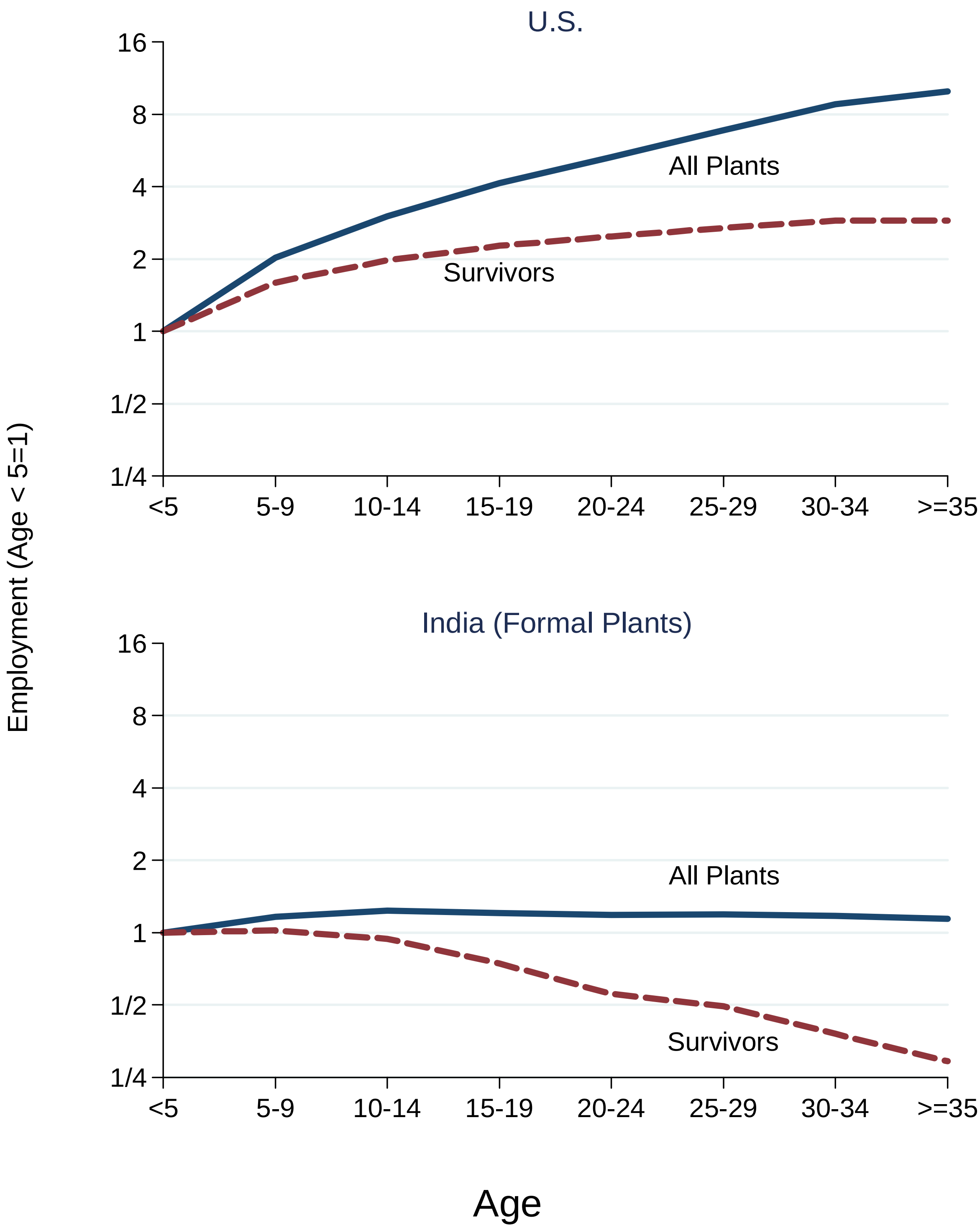
Figure 4: Employment Growth over the Life-Cycle



Notes: Employment growth with age imputed from 1992 and 1997 US Manufacturing Census, 1998 and 2003 Mexican Economic Census, and 1989-90 and 1994-95 Indian ASI-NSS.

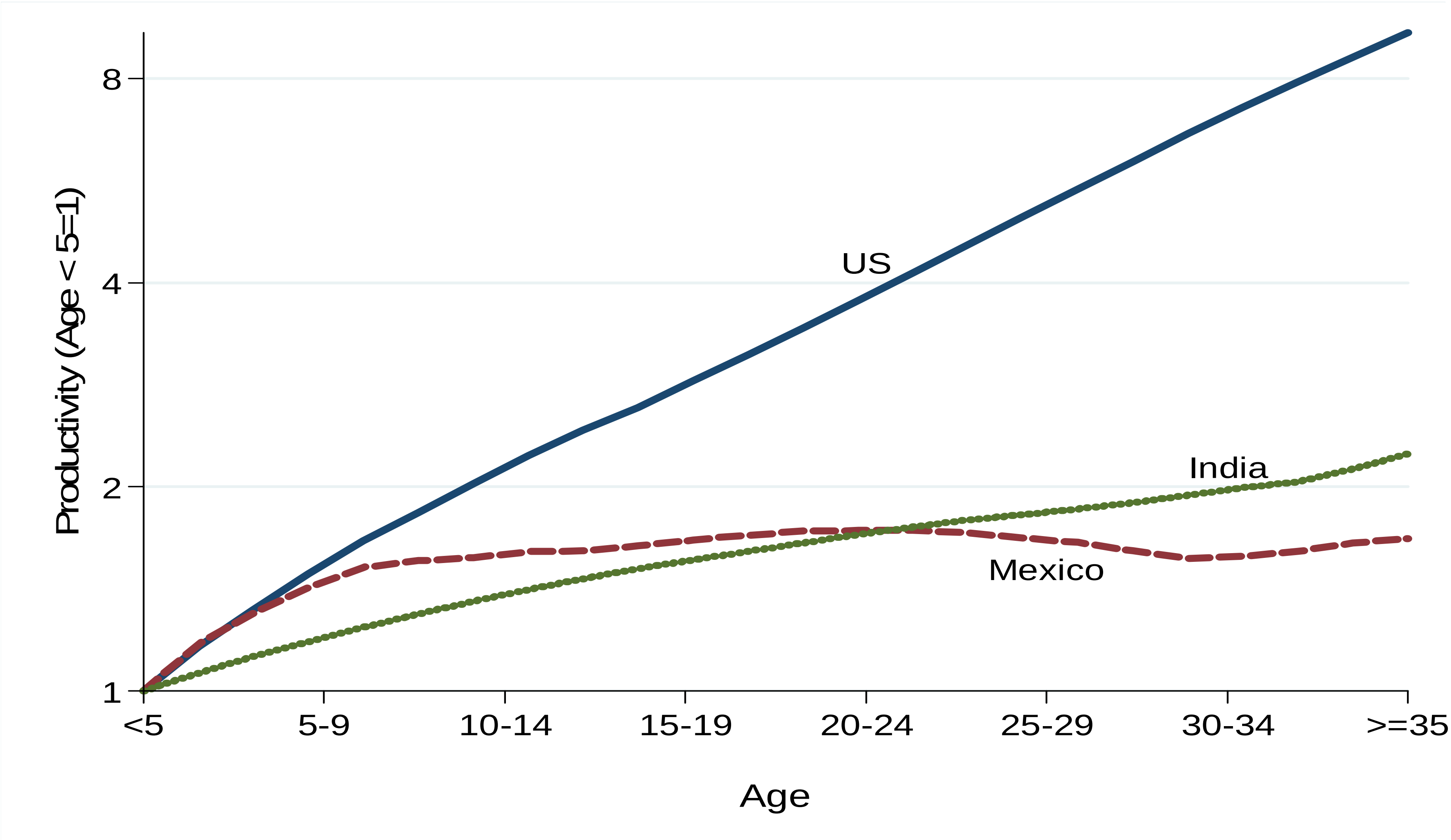
Figure 5: Employment Growth over the Life-Cycle

All Plants vs. Survivors



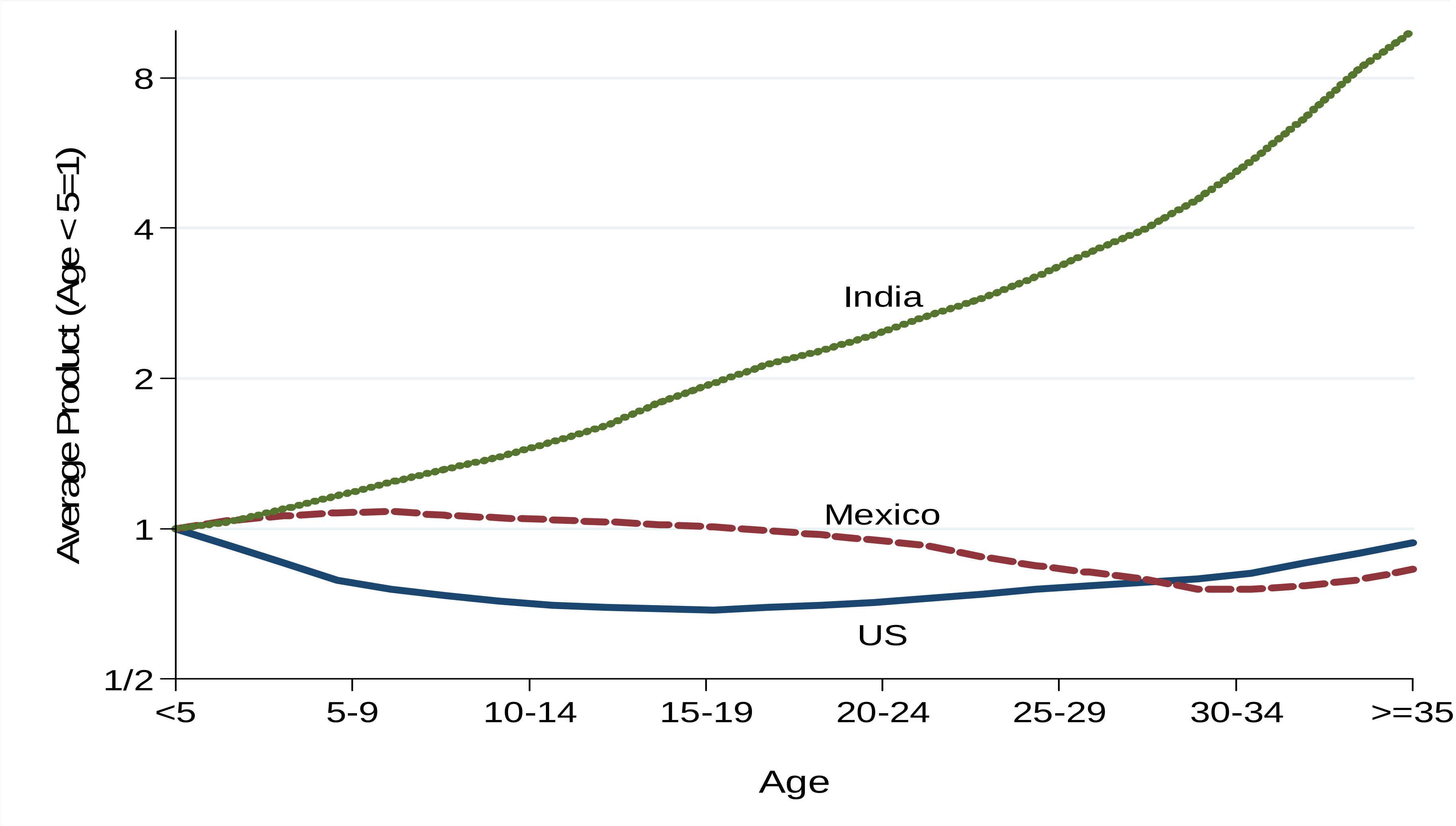
Note: Employment growth with age imputed from 1992 and 1997 US Manufacturing Census and 1998-89 and 2003-04 Indian ASI. Survivors are plants that exist in the two years.

Figure 6: Productivity Over the Life-Cycle



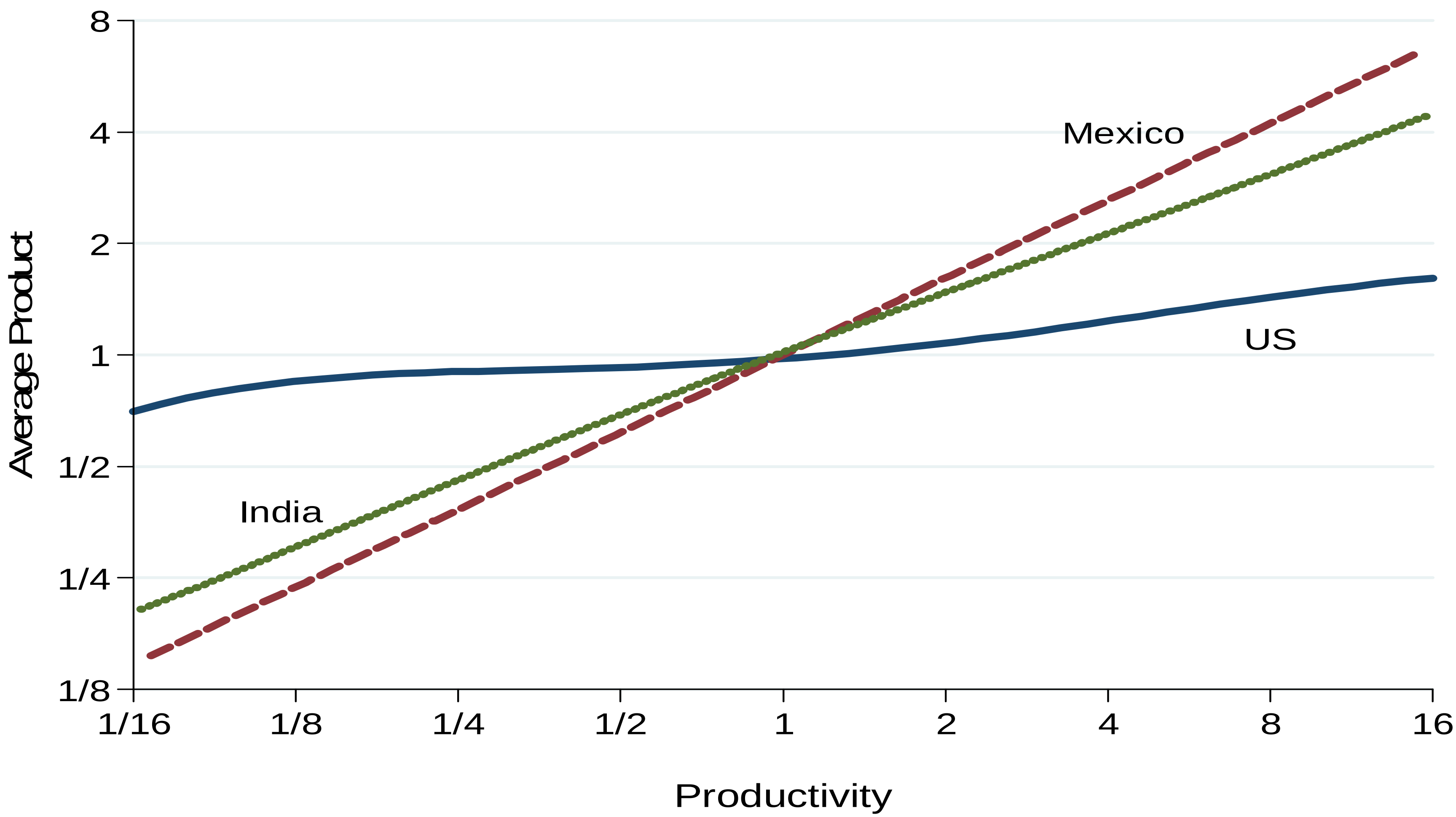
Note: : Productivity growth with age imputed from 1992 and 1997 US Manufacturing Census, 1998 and 2003 Mexican Economic Census, and 1989-90 and 1994-95 Indian ASI-NSS.

Figure 7: Average Product Over the Life-Cycle



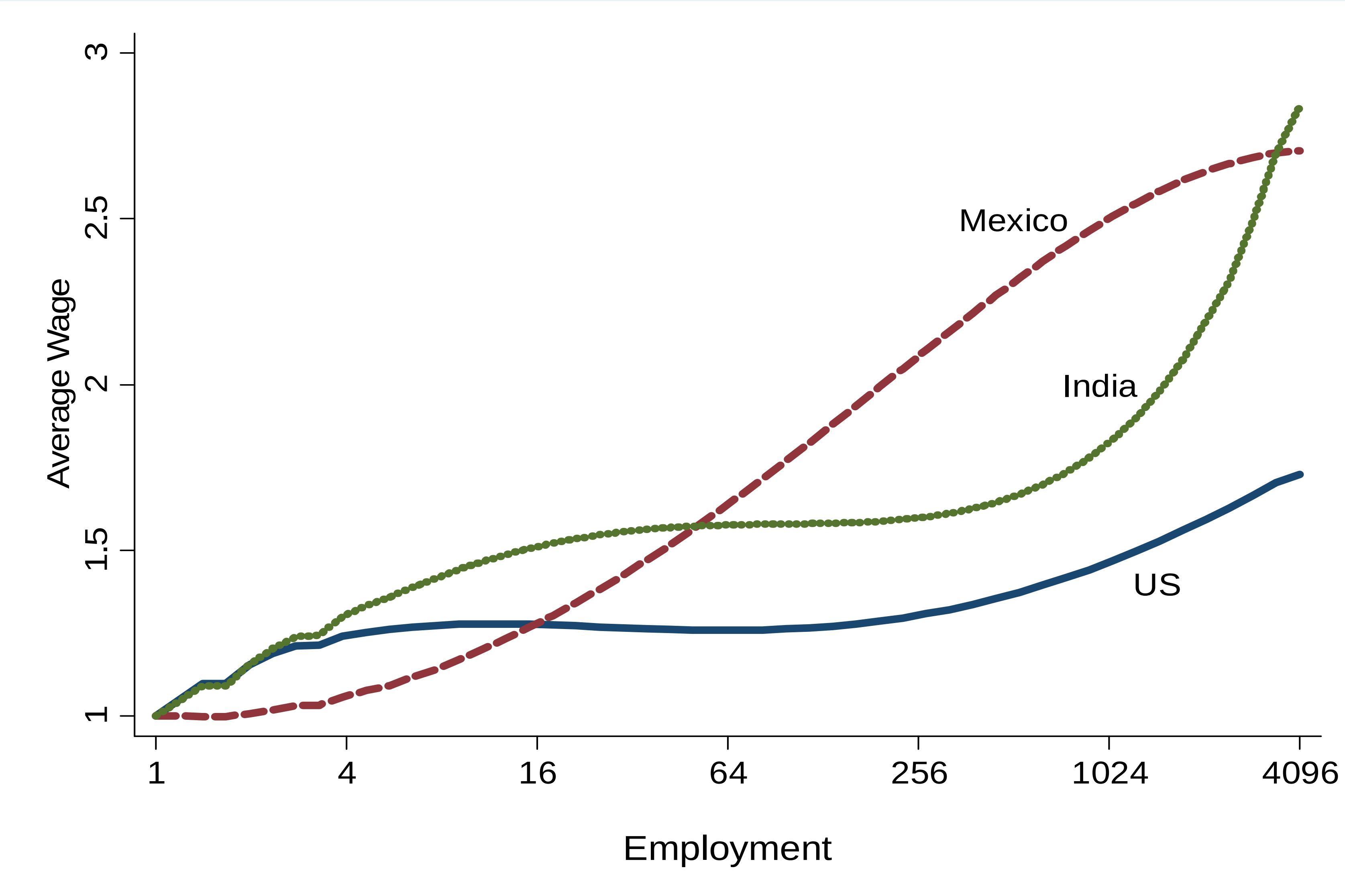
Notes: Average Product growth with age imputed from 1992 and 1997 US Manufacturing Census, 1998 and 2003 Mexican Economic Census, and 1989-90 and 1994-95 Indian ASI-NSS.

Figure 8: Average Product vs. Productivity in the Cross-Section



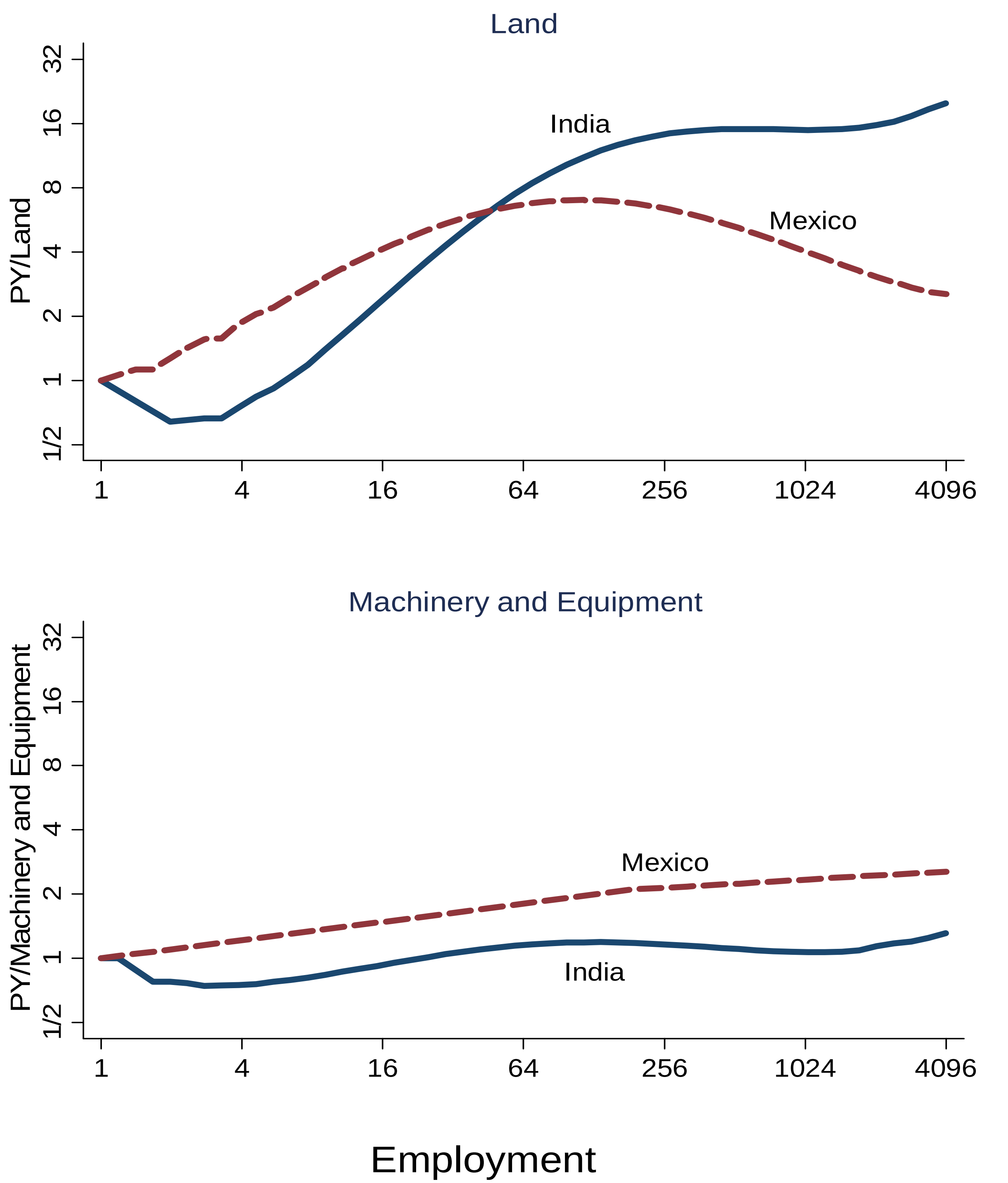
Note: τ and A are relative to weighted average of industry τ and A. Sources: 1994-95 ASI-NSS (India), 2003 Economic Census (Mexico), and 1992 Manufacturing Census (US).

Figure 9: Average Wage vs. Establishment Size



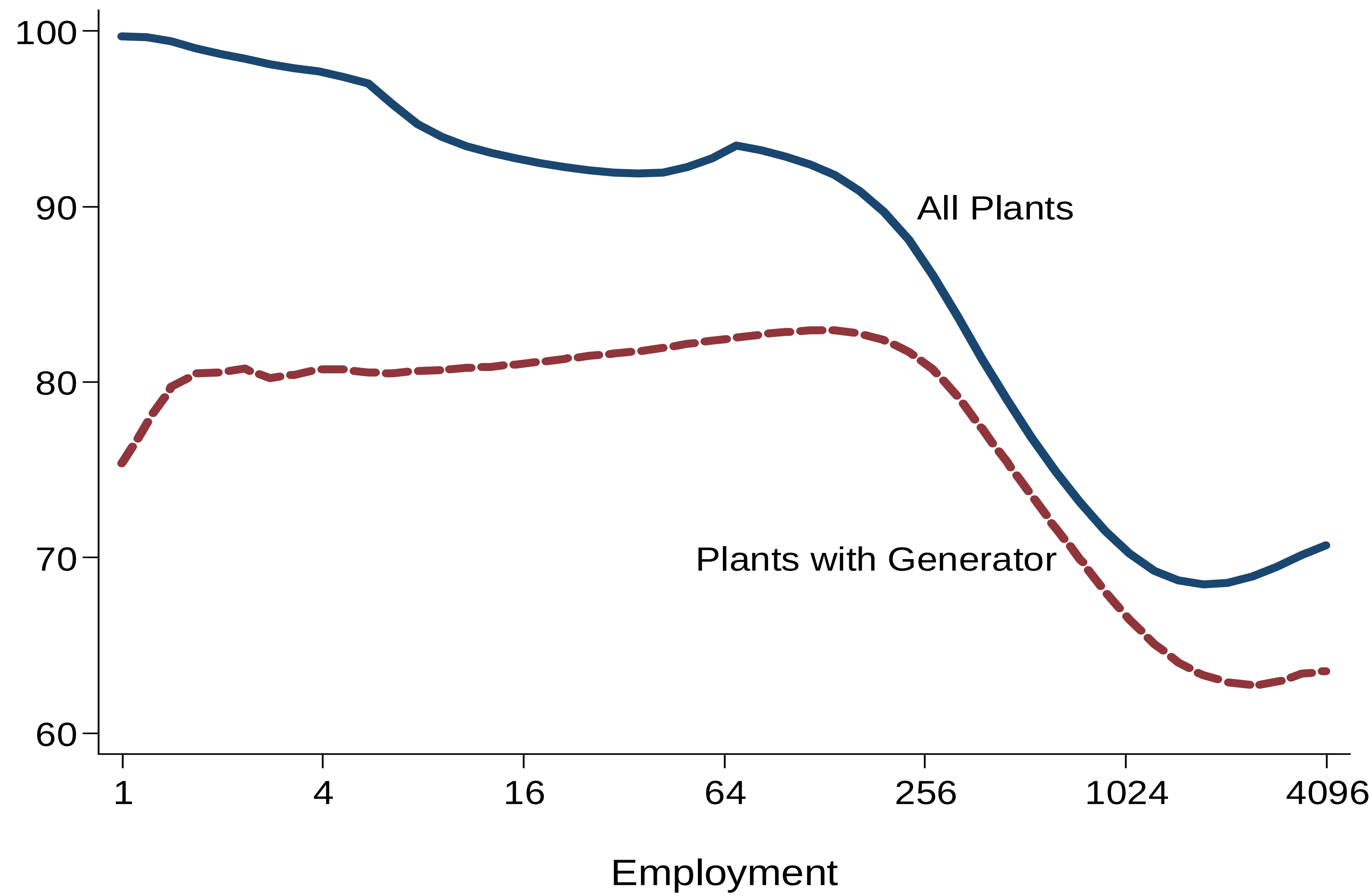
Sources: 1994-1995 ASI-NSS (India), 2003 Economic Census (Mexico), and 2002 Manufacturing Census (US

Figure 10: Average Productivity of Land and Machinery and Equipment



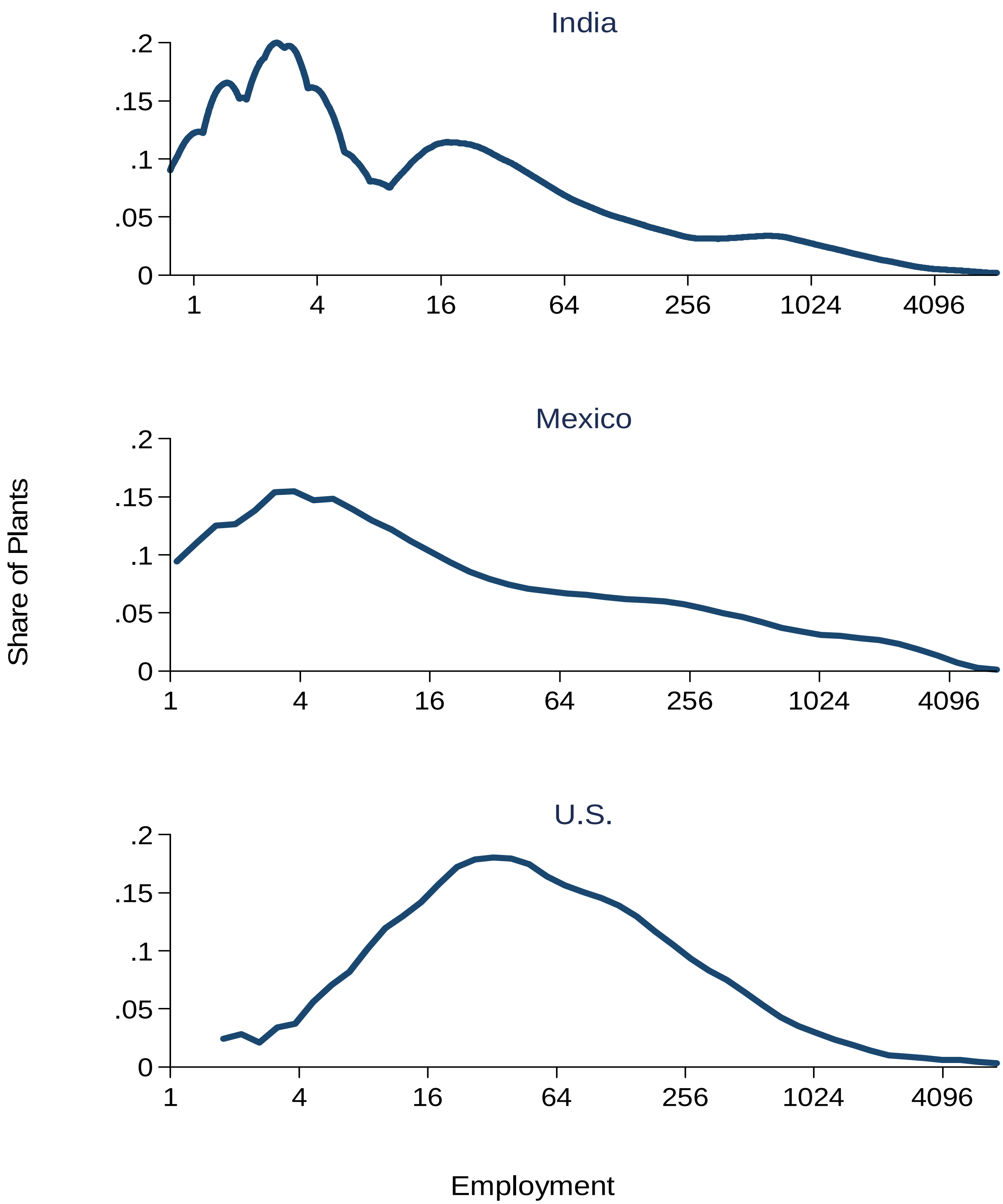
Sources: 1994-1995 ASI-NSS (India) and 2003 Economic Census (Mexico).

Figure 11: % Electricity Purchased from Grid in India



Source: 1994-1995 ASI.

Figure 12: Distribution of Establishment Size



Sources: 1989-90 ASI-NSS (India), 1998 Economic Census (Mexico), and 1997 Manufacturing Census (US).

Appendix:

Here we sketch two models that endogenously generate a positive elasticity of average product with respect to productivity. In the first model the number of management "layers" of the firm is determined endogenously as a function of firm productivity. In the second model, high productivity firms sell to a larger number of domestic markets.

<u>Management Costs</u>

Aggregate output is a C.E.S. aggregate of individual firm output:

$$Y = \left(\int_i Y_i^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}}$$

Firm output is given by:

$$Y_i = A_i \left(\int_{j=0}^{n_i} \left(a_j L_{ji} \right)^{\frac{\mu-1}{\mu}} dj \right)^{\frac{\mu}{\mu-1}}$$

Here, *j* indexes the management "layer" of the firm and n_i denotes the total number of layers. We order *j* such that it is increasing in $\frac{w_j}{a_j}$ where w_j is the price of layer *j* labor. We parameterize this relationship as $\frac{w_j}{a_j} \propto j^{\theta_w+\theta_a}$ where $w_j \propto j^{\theta_w}$ and $\frac{1}{a_j} \propto j^{\theta_a}$. Bloom et. al. (2011) suggests that the cost of adding management layers may be high in India. We model this as a large value of θ_a or θ_w in India. "Higher" management layers are less productive in India than in the US, which is captured by a large value of θ_w. Managers can also be more expensive in India, which is captured by a large value for θ_w.

The marginal increase in profit from an increase in n_i is

$$MB(n_i) \propto \frac{A_i^{\sigma-1}}{n_i^{1+(\theta_w+\theta_a)(\sigma-1)-\frac{\sigma-1}{\mu-1}}}$$

Assuming a fixed cost of each management layer and equating this cost with the marginal benefit, we get:

$$n_i \propto A_i^{\frac{\sigma-1}{1+(\theta_w+\theta_a)(\sigma-1)-\frac{\sigma-1}{\mu-1}}}$$

This says that high productivity firms establish more management layers. Importantly, the elasticity of n_i with respect to A_i is decreasing in θ_a and θ_w. Correspondingly, the increase of profit from a proportional increase in A_i is lower when θ_a or θ_w are larger.

Average revenue per worker is

$$\frac{P_i Y_i}{L_i} \propto A_i^{\frac{1}{\frac{1}{\theta_w+\theta_a}\left(\frac{\mu-\sigma}{(\mu-1)(\sigma-1)}\right)+1}}$$

and the average wage is

$$\overline{w}_i \propto L_i^{\frac{1+\theta_w}{1-\theta_a-\theta_w}}.$$

The elasticity of average revenue with respect to A_i and the elasticity of the average wage with respect to firm employment are increasing in θ_a and θ_w.

<u>Transportation Costs</u>

Consider a country with a number of symmetric markets indexed by j. In each market, aggregate output is given by:

$$Y_j = \left(\int_i Y_{ji}^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}}$$

where Y_{ji} is output of firm *i* in market *j*. Total output of firm *i* is:

$$Y_i = \int_{j=0}^{n_i} Y_{ji} dj$$

where n_i denotes the number of markets firm *i* sells to. Firm *i*'s profits from selling in market *j* is

$$\pi_{ji} \propto \left(\frac{A_i}{1+\tau_j}\right)^{(\sigma-1)}$$

where τ_j is the cost of transportation to market *j*. We rank *j* such that transportation costs are increasing in *j*, which we parameterize as $\left(1+\tau_j\right)^{(\sigma-1)} \propto j^{\theta}$. The idea is that some markets are closer and others further away, where distance is indexed by *j* and θ parameterizes how transportation costs increase as a function of distance. Assuming a fixed cost of accessing each market, which we parameterize as $F(n_i) \propto n_i^{\alpha}$, the number of markets firm *i* sells to is:

$$n_i = A_i^{\frac{\sigma-1}{\theta(1+\alpha/\theta)}}$$

The number of markets firm *i* serves is increasing in A_i with an elasticity that is decreasing in transportation costs per distance (θ). High transportation costs lowers the profits from investing in higher A_i. It also affects the equilibrium relationship between revenue per worker and productivity:

$$\frac{P_i Y_i}{L_i} \propto A_i^{\frac{1}{1+\alpha/\theta}}$$

A high elasticity of transport cost with distance (high value of θ) increases the elasticity of average revenue per worker with respect to A_i.

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