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. This pattern holds across many industries and for formal and informal establishments alike. 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% in India and Mexico relative to the U.S.

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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] Atkeson and Kehoe (2005) suggest that this life cycle is driven by the accumulation of plant-specific organization 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 establishment-specific intangible capital accumulation over the life cycle for understanding differences in aggregate TFP between poor and rich countries. Specifically, we compare the life cycle of manufacturing plants in India and Mexico to that in 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 the U.S., forty year old manufacturing plants are almost eight times larger than plants under the age of five in terms of employment. In India, by contrast, old plants are no larger than young plants. In Mexico, 25 year old plants are more than 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 organization capital in India and Mexico than in the U.S.

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

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

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 within India and Mexico that make it more difficult to reach more distant 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, factor costs, or shipping barriers 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 for 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 illustrative model calculations incorporating these forces, moving from the U.S. life cycle to the Indian or Mexican life cycle 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. Section VI concludes.

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

[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.

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 data covering almost the entire distribution of employment by establishment age.

For the U.S., we use data from the Manufacturing Census every five years from 1963 through 2002. The U.S. Manufacturing Census is a complete enumeration of manufacturing establishments with paid employees. It does not include manufacturing establishments that do not have paid employees.[3] 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.[4] 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 datasets we use for Indian manufacturing are 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.[5] The NSS is a survey of informal establishments conducted every five years as one of the modules of the Indian National

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[3] Such non-employee establishments accounted for only 0.29 percent of total manufacturing sales in 2007.

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

[5] 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.

Sample Survey. The ASI and the NSS collect data over the fiscal year (April 1 through March 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.[6] 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 & equipment and the value of land), value added, industry, and establishment age.[7] 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 1989-1990 and 1994-1995 in the NSS. Establishment identifiers are provided in the ASI starting in 1998-1999; 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 Census 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.[8] The variables we use from this data are the number of paid employees, contract workers, unpaid workers, hours worked (for each type of worker),

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[6] 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.

[7] 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 1989-1990, 1994-1995, and 2005-2006.

[8] 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.

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.[9] 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 around 75 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 average plant employment and age in the cross-section (Figure 1). The data is from the 1994-1995 ASI-NSS for India, 2003 Economic Census for Mexico, and 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.

The fact that older plants in India and Mexico are small may not have a large effect on aggregate outcomes if there are fewer surviving old plants in India and Mexico. Exit rates could

[9] 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, we computed the total number of manufacturing workers in the labor force survey was 35.7 million in 1999-2000 and 46 million in 2004-2005 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.

be higher in India and Mexico so fewer plants survive to old age. Figure 2, however, shows that exit rates in India and Mexico are generally no higher than in the U.S.[10] In addition, if growth rates over the life-cycle are highly skewed and only a small number of establishments experience high growth rates, the small number of rapidly growing establishments may have an important aggregate effect even if the *average* old establishment is small. Figure 3 addresses this concern by showing the distribution of employment by establishment age. The employment distribution by establishment age is a function of the relationship between the *employment-weighted* average of plant employment by age, 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 relationship between the employment-weighted average of plant employment and age in the cross section.

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. In sum, these facts indicate that just as the un-weighted average of plant-employment is increasing in age in the U.S. and not in Mexico and India (Figure 1), the employment-weighted average of plant employment is also increasing with age in the U.S but not in Mexico and India.[11]

These patterns are remarkably robust. We see a similar relationship between average size and age in all the other years for which we have data, when we measure plant size by value added (instead of employment), or when we use U.S. value added shares to aggregate the

[10] This allays a concern about combining NSS and ASI data. Namely, it is possible that ASI respondents report their establishment's age from when it became *formal*. We might therefore understate the age of larger ASI plants relative to smaller NSS plants, biasing our portrait of life cycle growth. If this was a major issue, however, then we would expect higher exit rates for Indian plants than U.S. plants *ceteris paribus*, which we do not see in Figure 2.

[11] Figure 3 also diminishes the concern that our data does not include street vendors in Mexico and non-employee establishments in the U.S. Although there are many such establishments, they are probably less important in terms of employment so that including them would not materially change the distribution of employment by age.

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. Also, we see flat size with respect to age in the formal plants of the Indian ASI alone, just as in the pooled NSS-ASI data.[12]

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 1989-1990 and 1994-1995 so we can only follow each cohort over these five years. 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 1989-1990 with the size of the same cohort five years later (in 1994-1995). 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 1989-1990 to 1994-1995. 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.[13]

Figure 4 presents the life cycle of plant employment calculated in this manner. In India, the over-time evidence suggests that, by age 35, average plant employment falls to *one-fourth* of

[12] An interesting question is whether the life-cycle of *firm* employment differs between the U.S. and Mexico and India. We do not have data on firms in the Mexican and Indian data so we cannot answer this question. However, starting in 2001-2002, the Indian ASI provides information on the number of other establishments owned by the same firm. This information indicates that an average 40 year old plant is owned by a firm that operates 0.76 more plants than the owner of a newborn plant. In addition, a regression of log employment on the number of additional establishments operated by the plant's owner yields a coefficient of 0.068 on the number of additional establishments. These two numbers suggest that employment of the average 40 year old firm is 0.81 (0.76*exp(0.068)) larger than employment of a newborn firm.

[13] 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.

its level at birth. The evidence from cross-sectional data indicated 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 suggested less than an eight-fold increase. In Mexico, the over-time evidence is similar to what the cross-section implied for the 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 similar to those shown in Figure 4.

Growth in average employment of a cohort can be driven by survivor growth and/or by the exit of small establishments. Several authors, including Jovanovic (1982), Hopenhayn (1992), Ericson and Pakes (1995) and Luttmer (2007), model the evolution of the U.S. life cycle via the selection mechanism rather than survivor growth. We now explore whether the selection effect could explain 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 1998-1999 to 2003-2004 (we have establishment identifiers in the ASI starting in 1998-1999). 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 is negatively correlated with size in both countries. The contribution of selection to 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) in India compared to 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 plants 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)
$$\pi_{a,i} = (1-\tau_{Y_{a,i}})P_{a,i}Y_{a,i} - (1+\tau_{L_{a,i}})wL_{a,i} - (1+\tau_{K_{a,i}})RK_{a,i} ,$$

where $P_{a,i}$ is the plant-specific output price, $L_{a,i}$ is the plant's labor input, $K_{a,i}$ the plant's capital stock, and *w* and *R* are the common, undistorted costs of labor and 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 may arise for any number of reasons, such as taxes, markups, adjustment costs, transportation costs, size restrictions, labor regulations, and financial frictions.[14]

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. $A_{a,i}$ is process efficiency here for concreteness, but in terms of the available data it is 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) $$P_{a,i} Y_{a,i} \propto \left(\frac{A_{a,i}}{\tau_{a,i}} \right)^{\sigma-1}$$

(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 geometric average of the average revenue products of capital and labor. Equation (1.5) holds if the ratio $\tau_{K_{a,i}} / \tau_{L_{a,i}}$ does not vary across plants. See Hsieh and Klenow (2009) for additional details. We are building on the work of Foster, Haltiwanger and Syverson (2008), who distinguish between TFPR (revenue TFP, $\tau_{a,i}$ here) and TFPQ (quantity TFP, $A_{a,i}$ 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 revenue 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. The *growth* of plant revenue and employment with age then depends on the growth of plant productivity with age and the extent to which plant average products change with age.

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

We need data on PY, K, L, and α to measure plant productivity and average products. We measure PY as plant value-added, K as the book-value of the plant's capital stock, and $1-\alpha$ as the U.S. wage-bill share of the sector. In Hsieh and Klenow (2009), we measure L as the plant's wage-bill. We do not do so here because a large number of establishments in India and Mexico do not have paid workers. For the U.S. we measure plant employment as the total number of workers. For 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). For 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. More exactly, Figure 6 plots 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. For Mexico and the U.S. 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), average products must be rising with age in India to explain these two facts. Figure 7 plots the geometric average of the average product of capital and labor over the life cycle. In India, average products of capital and labor are 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, in Mexico and the U.S. employment grows with age 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 a random draw of initial 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 increase in variable profits from a proportional increase in productivity is

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

As shown, the return from investment in organization capital is increasing in the ratio of productivity to τ. Thus the elasticity of τ with respect to productivity will affect the profitability of investing in higher productivity. 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 in the cross-section for each of our three countries. τ rises much more steeply with productivity in India and Mexico than in the U.S. In India and Mexico, a doubling of establishment productivity is associated with a 50-60 percent increase in the average product of factor inputs. In the U.S. a doubling of productivity is associated with a 10 percent gap in average products. Rising average products 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 or higher effective tax rates 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 with family workers. Labor regulations and labor 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 plants, 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 U.S.

If labor costs are more convex with size in India and Mexico, we expect to see more plants choosing to remain small and informal. Table 2 presents details on the prevalence of informal and family-owned establishments in the Indian and Mexican manufacturing sectors. Here, we define family establishments in India and Mexico as those that *only* employ unpaid workers and informal establishments as those not registered in India. For Mexico, we define informal establishments are 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 1989-1990. The employment share of family owned plants 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 are also higher in large plants in India and Mexico, but the gap in average wages between large and small establishments there 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 there. Frictions in land markets may also prevent high productivity plants 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. The average product of land is rising with establishment size in India. This could be evidence of technological differences (larger establishments use less land-intensive techniques), but it can also be evidence that frictions to land reallocation raise the marginal cost of land faced by high productivity plants. 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. And in India the average product of machinery and equipment is 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.[15] In 1994-1995, for example, about one-third of formal Indian establishments report owning a generator. Figure 11 plots the establishment's electricity purchased from the grid as a percent of its total consumption of electricity against 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 for large plants. This evidence suggests that the supply of power from the electric grid is limited so that larger plants must rely on higher unit-cost generators.

The returns to innovation could also be concave in India and Mexico compared to the U.S. Income or sales taxes that apply to large establishments are an obvious candidate explanation. If corruption disproportionately affects large establishments, this would also have the same effect.[16] Another possibility 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 the Appendix we sketch a model with a continuum of markets that differ in distance from plants. In this framework, higher shipping costs per unit of distance lowers the number of markets a firm with a given level of productivity serves. In turn, this lowers the returns from investing in higher productivity.

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

[16] La Porta and Shleifer (2008) document that larger formal establishments spend more on bribes (as a share of revenue) than do smaller and informal establishments.

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 a useful direction for future work, but we will not attempt to do so here. Instead, we merely want to stress how the elasticity of τ with respect to productivity, whatever the source, affects the incentive to invest in projects that boost firm productivity. The cross-sectional relationship between τ and productivity is consistent with the hypothesis of lower returns to investing in productivity in Mexico and India than in 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 and Mexican life cycle productivity on the level of aggregate productivity.[17] We do this for a sequence of simple GE models built around monopolistic competitors with life cycle productivity. In addition to Melitz (2003), we follow Atkeson and Burstein (2010) in many of our modeling choices. 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 a fixed real interest rate

[17] Cole, Greenwood and Sanchez (2011) also construct a quantitative model to fit our facts for India, Mexico and the U.S. In their model financing frictions inhibit incumbent technology adoption in India and Mexico.

See Luttmer (2010) as well as Atkeson and Burstein (2010) for the derivations.

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

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

where $Y_{a,i} = A_{a,i} L_{a,i}$ and $\tau_{a,i} = P_{a,i} Y_{a,i} / L_{a,i} = P_{a,i} A_{a,i}$. As these models do not have capital, we assume a single revenue distortion hits each plant, with average value $\bar{\tau}$.[18]

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 is the sum of production labor across all plants, and L_R is the number of people working in the research sector to improve process efficiency for incumbents and come up with new varieties for entrants.

We start by assuming the flow of entrants is fixed over time, and requires no labor. And we first imagine *A* varies only by age. All entrants have the same *A*, and then this productivity grows exogenously as an incumbent ages. Exit rates are exogenous, but depend on age. All firms face the same τ. In this case we simply get

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

Implicit in (1.7) is that labor is allocated to efficiently exploit variation in *A* across cohorts. We calculate aggregate TFP from (1.7) using U.S. *A* by age and, separately, with Indian and Mexican *A* by age. We fix the mass of entrants in each year to $N_1 = 1$, and keep the exit rates by age at the U.S. levels displayed in Figure 2.[19] Table 3 lists the parameter values chosen for this model and subsequent models.

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

[19] 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 for computational convenience.

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 28%. 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-third of the aggregate TFP difference (ln(0.72)/ln(0.38) ≈ 0.33).

This calculation assumes no response of entry to life cycle growth. In the data, average plant size is smaller in India (and Mexico) than in the U.S. Figure 12 plots the employment distribution by plant size in the three countries to illustrate this fact. As exit rates are no lower in India and Mexico, their entry rates must be higher. This might 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) find that slower productivity 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 future profits at the time of entry. Entry therefore increases 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* among operating firms.[20]

The second column in Table 4 shows what happens with endogenous entry when moving from U.S. to Indian life cycle growth. Average firm *A* falls by the same amount, 28%, by construction. But now entry rises 21%. The net effect on aggregate TFP is still negative at -26%. Even with our low substitutability ($\sigma = 3$) and therefore a strong love of variety, 21% more variety lifts aggregate TFP by less than 10%. And the additional entry diverts some labor from goods production, lowering the share of people producing current output by over 6%. Still, on net the variety response does offset some of the TFP loss from lower life cycle productivity growth. Fattal Jaef (2012) obtains 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 requires twice as much entry labor. If there are instead diminishing returns of some form, then variety might not respond as flexibly. We will provide a

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[20] 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.

specific example below. Second, the model assumes a final goods sector which buys some of every variety. Yet many small manufacturers in India – for example those making food and furniture – may sell 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) posits convex costs of accessing buyers within countries; see the model in our Appendix inspired by his work.

We next add productivity (A) dispersion within age cohorts, and distortions in the form of a revenue tax rate τ that is increasing in A. In India, the slope of τ with respect to A is much steeper at 0.56 than the U.S. slope of 0.13.[21] Again, this might reflect some combination of tax rates, size restrictions, labor regulations, markups and so on. The third column of Table 4 shows that going from U.S. to Indian life cycle productivity *and* distortions results in 51% lower average firm TFP. This loss is much higher than in the previous column because of the static misallocation created by greater τ dispersion across plants with different A levels in India than in the U.S.[22] Entry surges by 34%. As a result the share of the workforce producing output falls 10%. The net effect is a drop in aggregate TFP of 49%.

So far we have set the initial entrant A distribution to match the U.S. data. But across young plants, A is more dispersed in India and Mexico 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. In Mexico, the standard deviation log A is 1.46. Greater entrant A dispersion in India and Mexico could be a byproduct of greater entry there. 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 4 considers this case. We calibrated the mass of potential entrants to 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 larger drop in aggregate TFP of -64% (vs.

[21] 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. But the elasticity is 0.69 in Mexico, so there we actually infer *falling* employment in A.

[22] Although similar to the 40-60% range 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, whereas here we allow A to evolve differently with age.

49% in the previous column). The reason is that the average *A* of entrants falls, whereas it was previously held fixed. This helps drag down the average *A* of all plants by over 73% (vs. the 51% fall with a constant quality of entrants). Variety is up 50%, lowering plant size in the direction of India vs. the U.S. (Figure 12). The calibrated entry cost is now extremely small to explain why the low *A* marginal entrant has zero profits, so the surge of entry in this counterfactual requires little extra labor devoted to entry. But the net effect is still a much bigger drop in overall TFP. Thus endogenous entrant productivity could lead to even bigger TFP losses from slower life cycle productivity growth.

The final column in Table 4 endogenizes incumbent *A* growth *a la* Atkeson and Burstein (2010).[23] Here incumbents choose the probability q of taking a proportional step up vs. down in their *A*. (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 is

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

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. This 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 U.S. to Indian joint distribution of τ with *A* and age.

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.[24] The result is 53% lower *A* for the average plant. This is similar to what we imposed in the exogenous life cycle growth column. Thus the size distortions seen in India successfully induce the low life cycle productivity growth seen in India in this model. As entrants have less competition from incumbents, entry rises 62%. The share of the population working falls over 9%, even though some labor is freed up from doing innovation for incumbents. Aggregate TFP falls 46%. Unlike

[23] For simplicity we revert to zero expected profits for all entrants in this case.

[24] Again, this hinges on 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.

Atkeson and Burstein, the distortions hitting incumbents are not fully offset by entry. The reason is that we consider much larger distortions – based on Indian data – than the tariffs Atkeson and Burstein considered. Here entry is a poor substitute for such low innovation by incumbents.

Table 5 repeats the counterfactual calculations using the plant-level patterns from Mexico. Going from the U.S. to Mexican life cycle lowers aggregate TFP at least as much as in the Indian simulations. Here the endogenous innovation scenario actually overdoes it, generating unrealistically low life cycle growth for Mexico.

VI. Conclusion

In Hsieh and Klenow (2009) we provided suggestive evidence that, holding the distribution of plant productivity fixed, resource misallocation between existing plants can account for about one-third of the gaps in aggregate manufacturing TFP between the U.S. and countries such as China and India. 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) account for most of the gap in aggregate TFP between poor and rich countries.

In this paper, we take up the question left unanswered in our previous work. Why is average plant productivity lower in poor countries? We argue that a certain type of misallocation – 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 U.S. 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 or Mexican 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 possible barriers, 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 these potential driving forces 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., and the slope of exit 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

	Fixed Entry	Free Entry	τ and A Dispersion	Endogenous Entrant Quality	Incumbent Innovation
Weighted Average A	-28.5%	-28.5%	-51.3%	-73.5%	-53.3%
Entry	0%	+21.5	+33.6%	+50.0%	+62.5%
(Production Workers)/Workforce	0%	-6.2%	-9.9%	-0.0%	-9.6%
Aggregate TFP	-28.5%	-26.1%	-49.3%	-63.9%	-46.2%
Model Ingredients					
A variation by:	Age	Age	Age, WITHIN	Age, Within	Age, Within
τ variation by:	None	None	Age, WITHIN	Age, Within	Age, Within
Free Entry	No	**YES**	Yes	Yes	Yes
Endogenous Entrant Quality	No	No	No	**YES**	No
Incumbent Innovation	No	No	No	No	**YES**

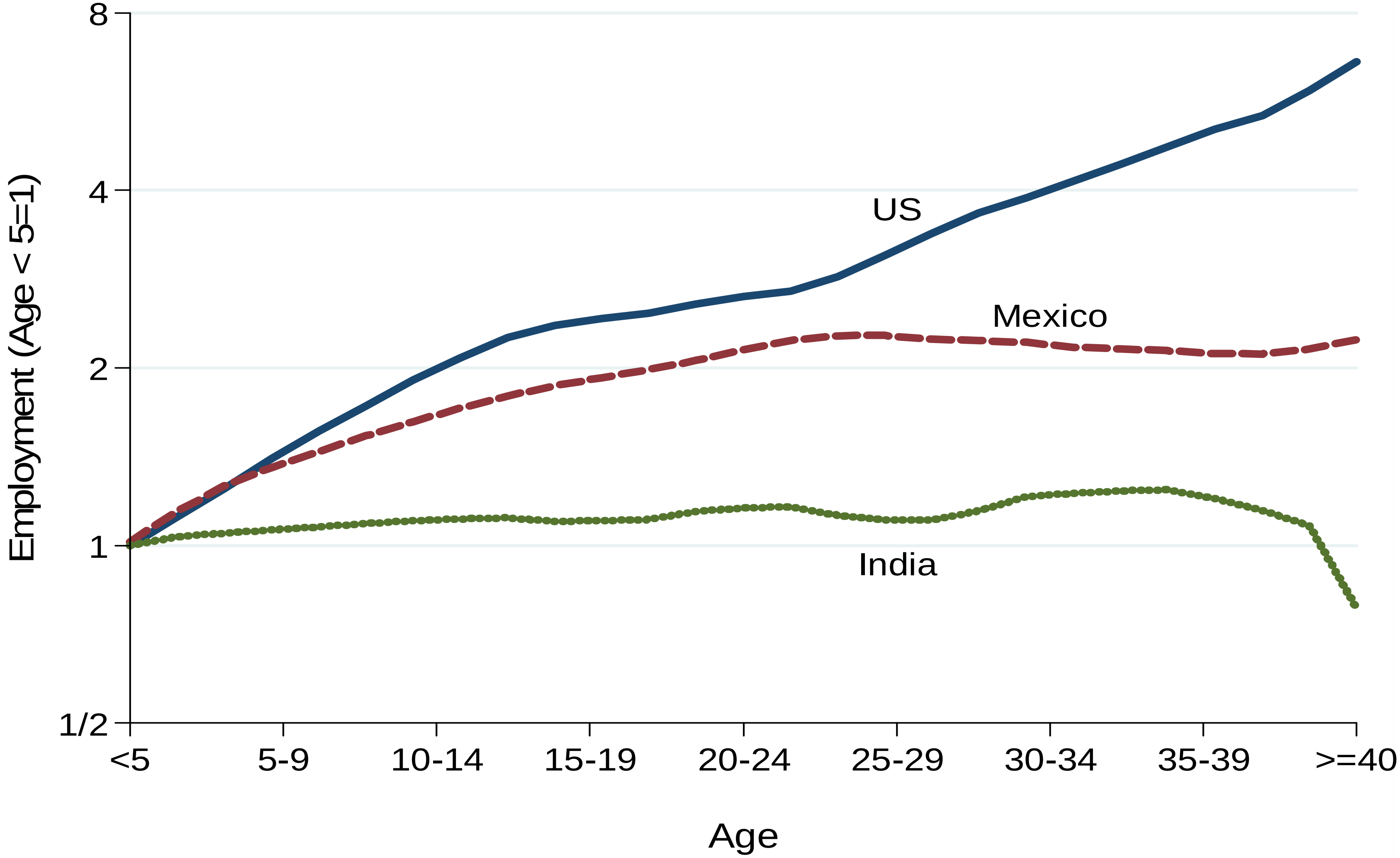
Source: Author calculations using code adapted from Atkeson and Burstein (2010). Exit varies by both age and *A* as in the U.S.

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

	Fixed Entry	Free Entry	τ and A Dispersion	Endogenous Entrant Quality	Incumbent Innovation
Weighted Average A	-28.3%	-28.3%	-63.8%	-80.5%	-75.6%
Entry	0%	+18.8	+14.9%	+42.5%	+26.4%
(Production Workers)/Workforce	0%	-5.5%	-5.1%	-0.0%	-2.3%
Aggregate TFP	-28.3%	-26.1%	-63.2%	-74.6%	-73.2%
Model Ingredients					
A variation by:	Age	Age	Age, WITHIN	Age, Within	Age, Within
τ variation by:	None	None	Age, WITHIN	Age, Within	Age, Within
Free Entry	No	**YES**	Yes	Yes	Yes
Endogenous Entrant Quality	No	No	No	**YES**	No
Incumbent Innovation	No	No	No	No	**YES**

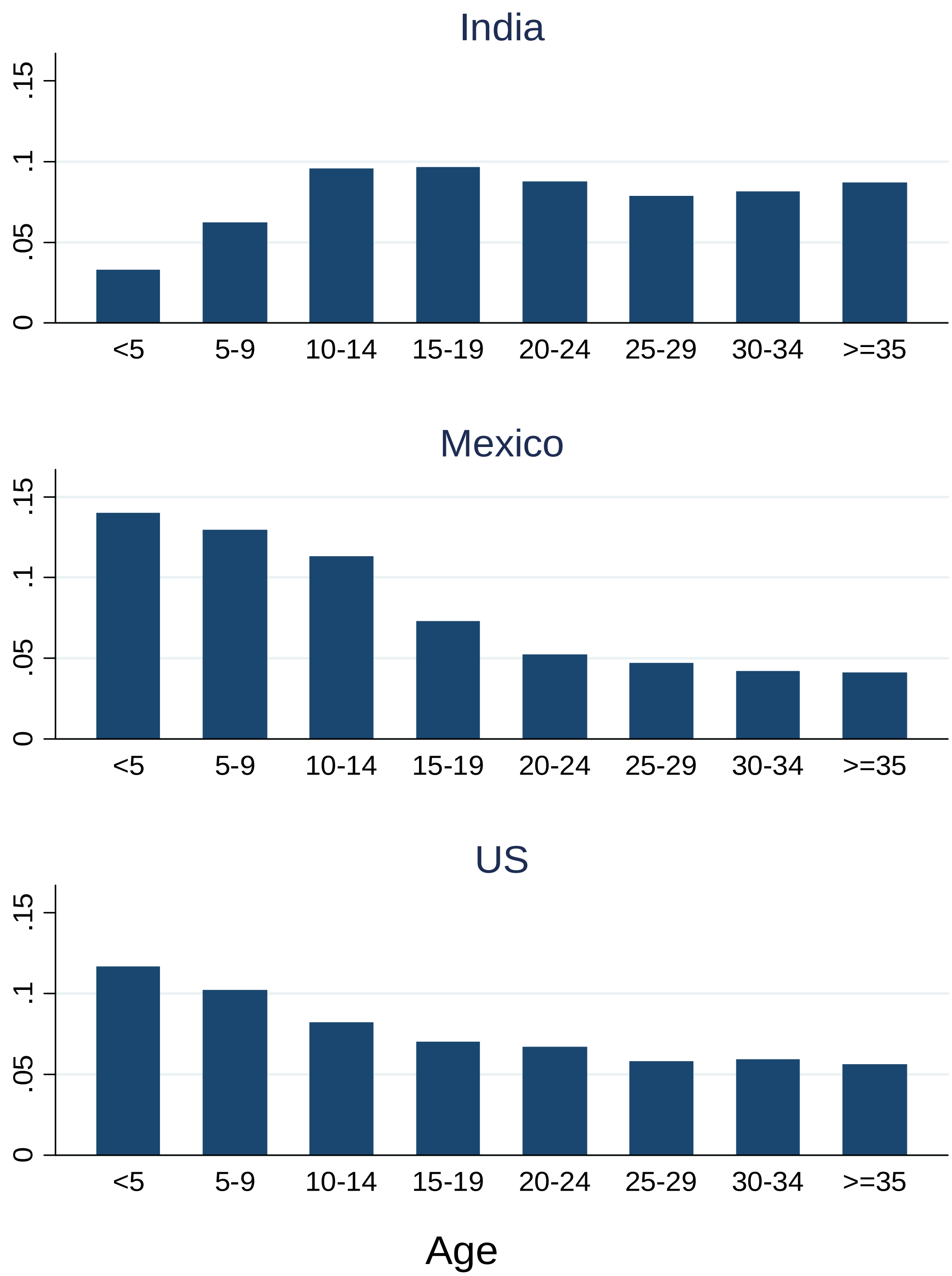
Source: Author calculations using code adapted from Atkeson and Burstein (2010). Exit varies by both age and *A* as in the U.S.

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



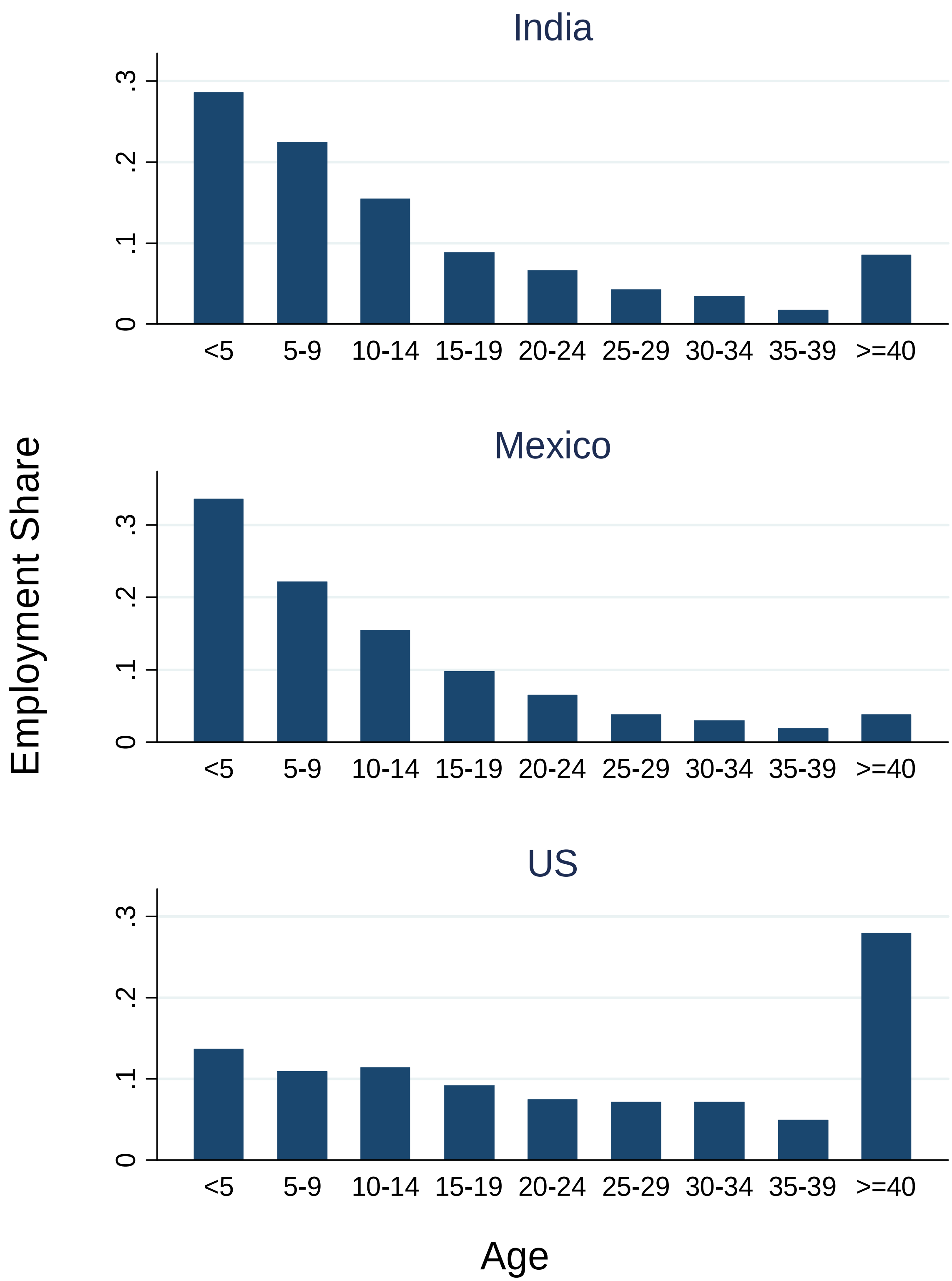
Sources: 1994-1995 ASI-NSS (India), 2003 Economic Census (Mexico), and 2002 Manufacturing Census (U.S.).

Figure 2: Exit Rate by Age



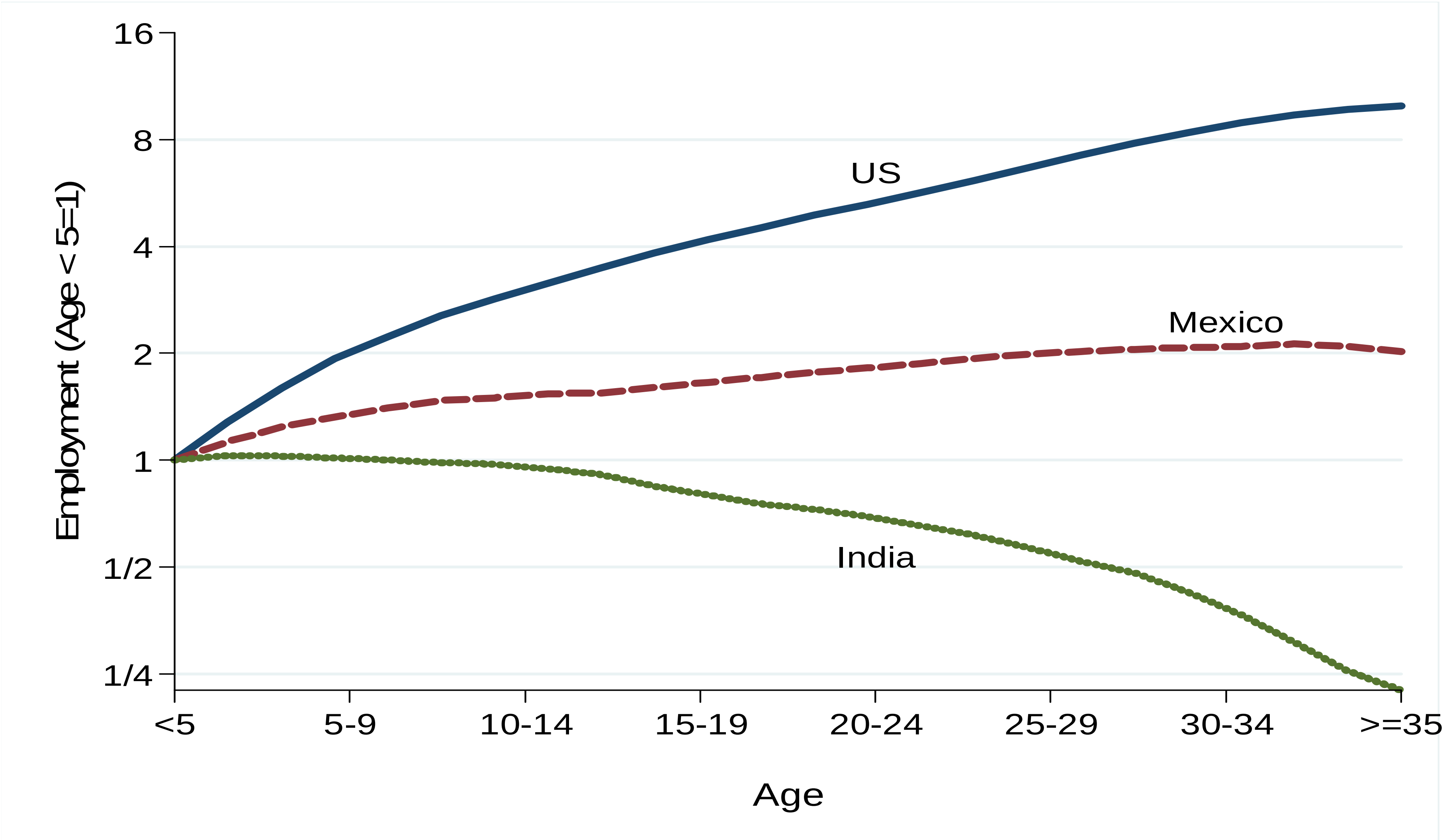
Notes: Exit Rate calculated from 1992 to 1997 (U.S. Manufacturing Census), 1989-1990 to 1994-1995 (India ASI-NSS), and 1998 to 2003 (Mexican Manufacturing Census).

Figure 3: Employment Share by Age



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

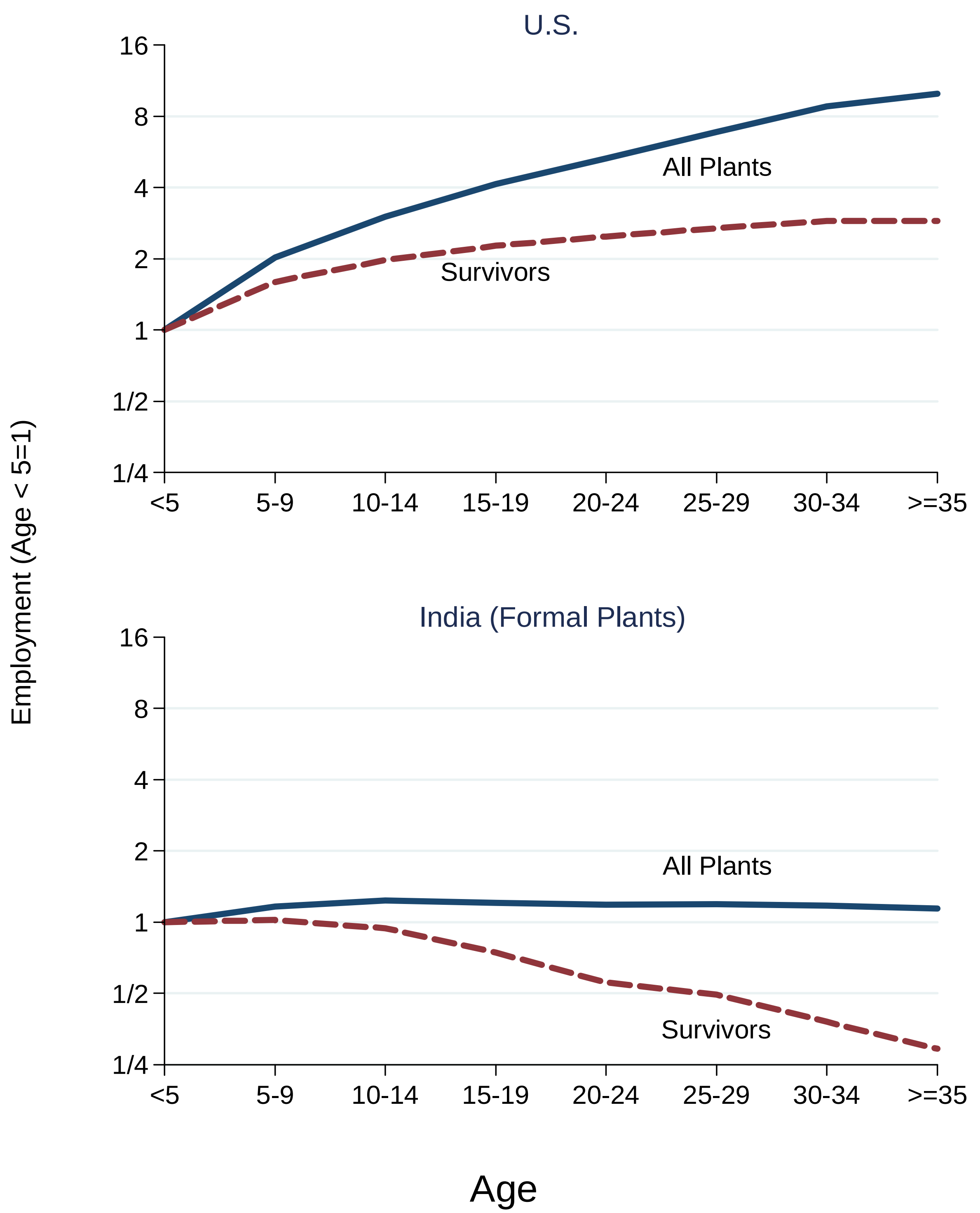
Figure 4: Employment Growth over the Life-Cycle



Notes: Employment growth with age imputed from 1992 and 1997 U.S. Manufacturing Census, 1998 and 2003 Mexican Economic Census, and 1989-1990 and 1994-1995 Indian ASI-NSS.

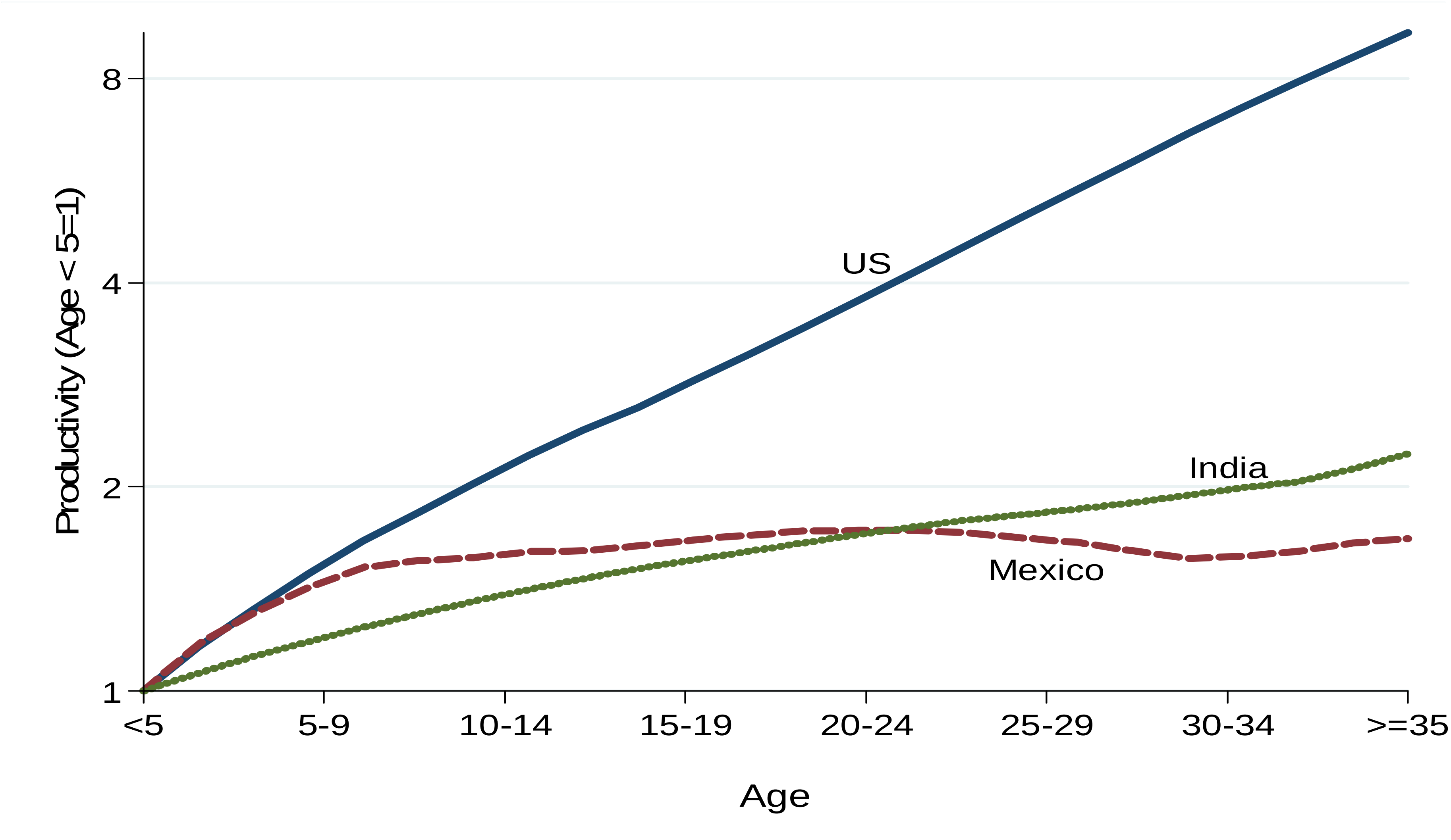
Figure 5: Employment Growth over the Life-Cycle

All Plants vs. Survivors



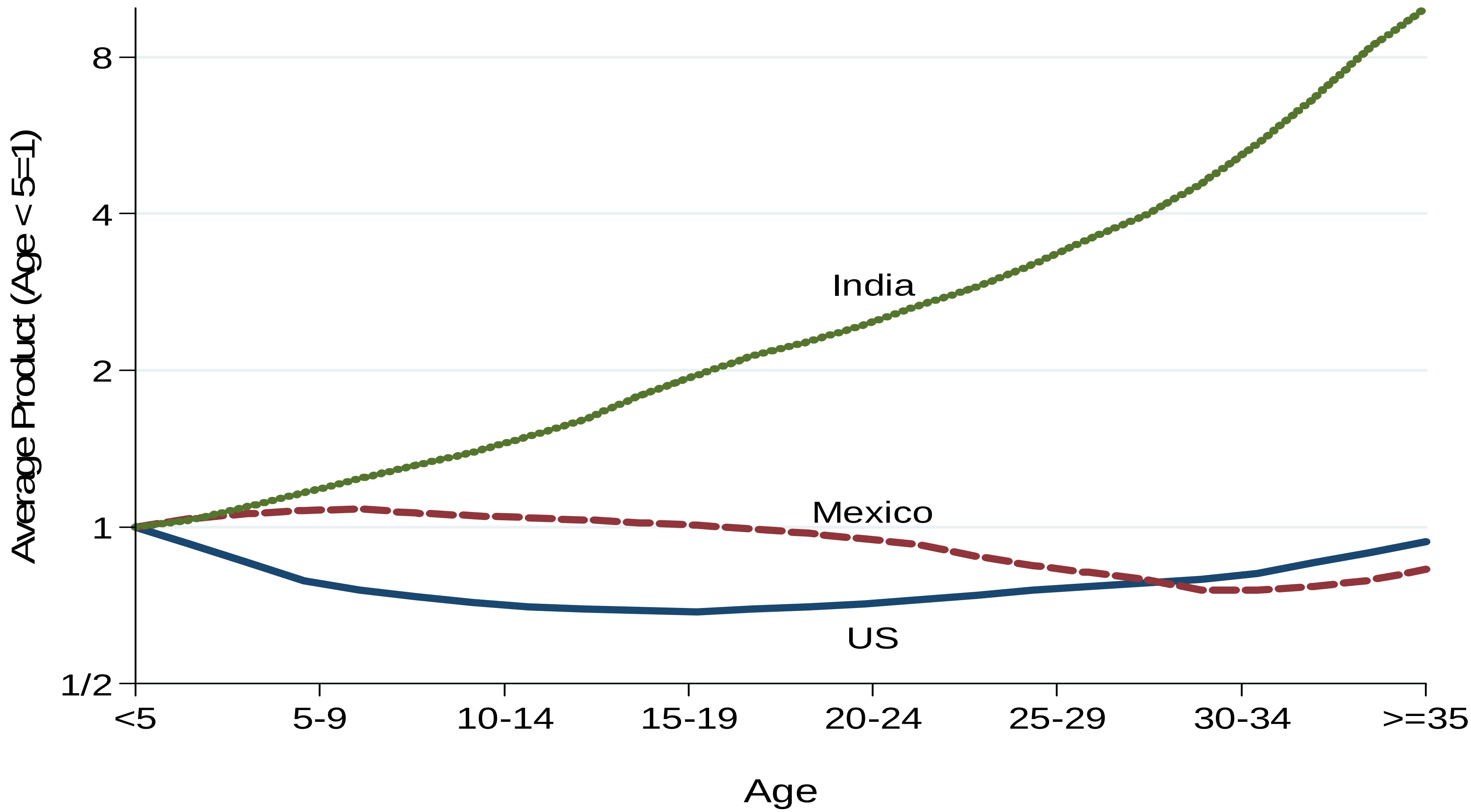
Note: Employment growth with age imputed from 1992 and 1997 U.S. Manufacturing Census and 1998-89 and 2003-2004 Indian ASI. Survivors are plants that exist in the two years.

Figure 6: Productivity Over the Life-Cycle



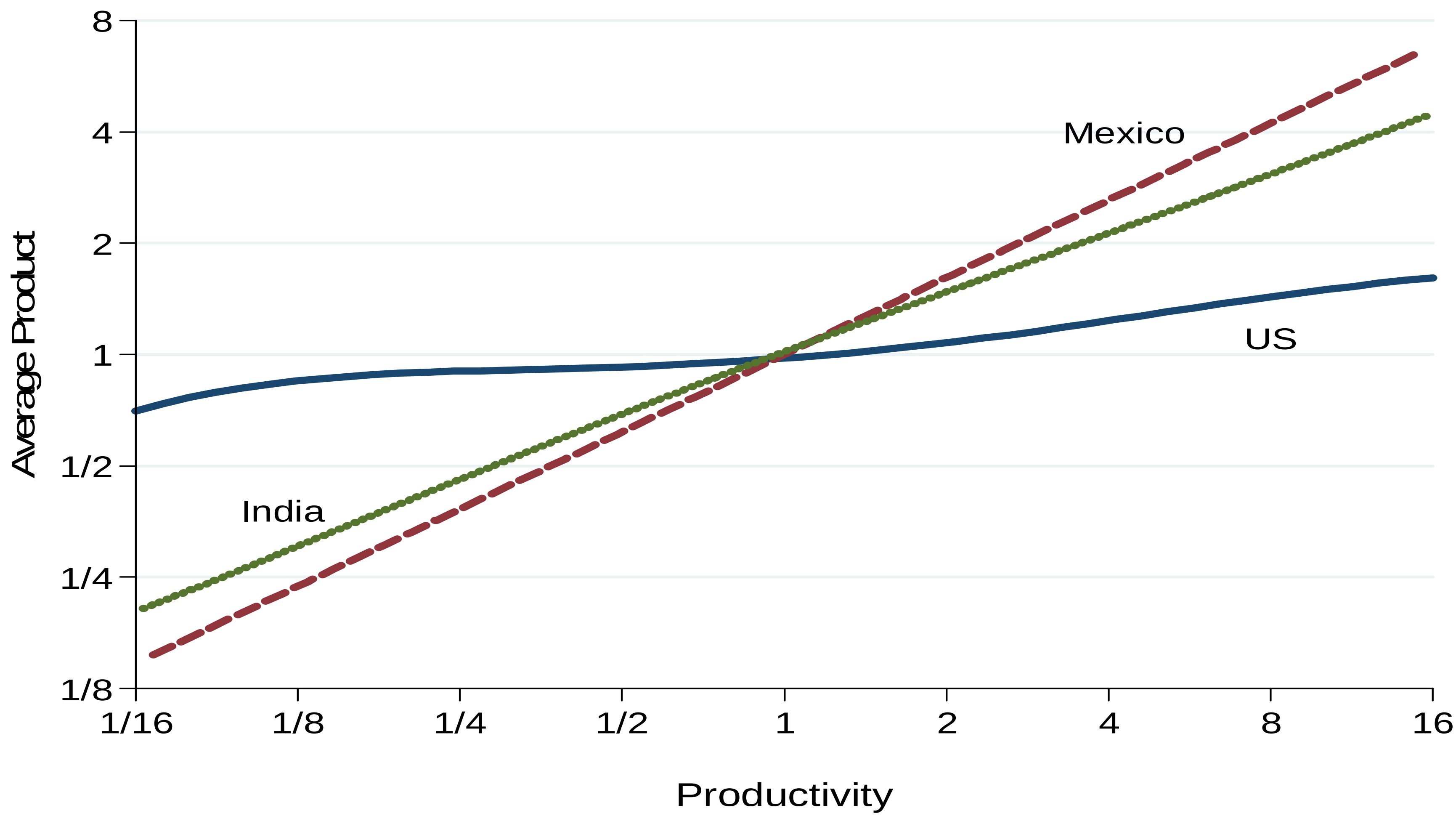
Note: : Productivity growth with age imputed from 1992 and 1997 U.S. Manufacturing Census, 1998 and 2003 Mexican Economic Census, and 1989-1990 and 1994-1995 Indian ASI-NSS.

Figure 7: Average Product Over the Life-Cycle



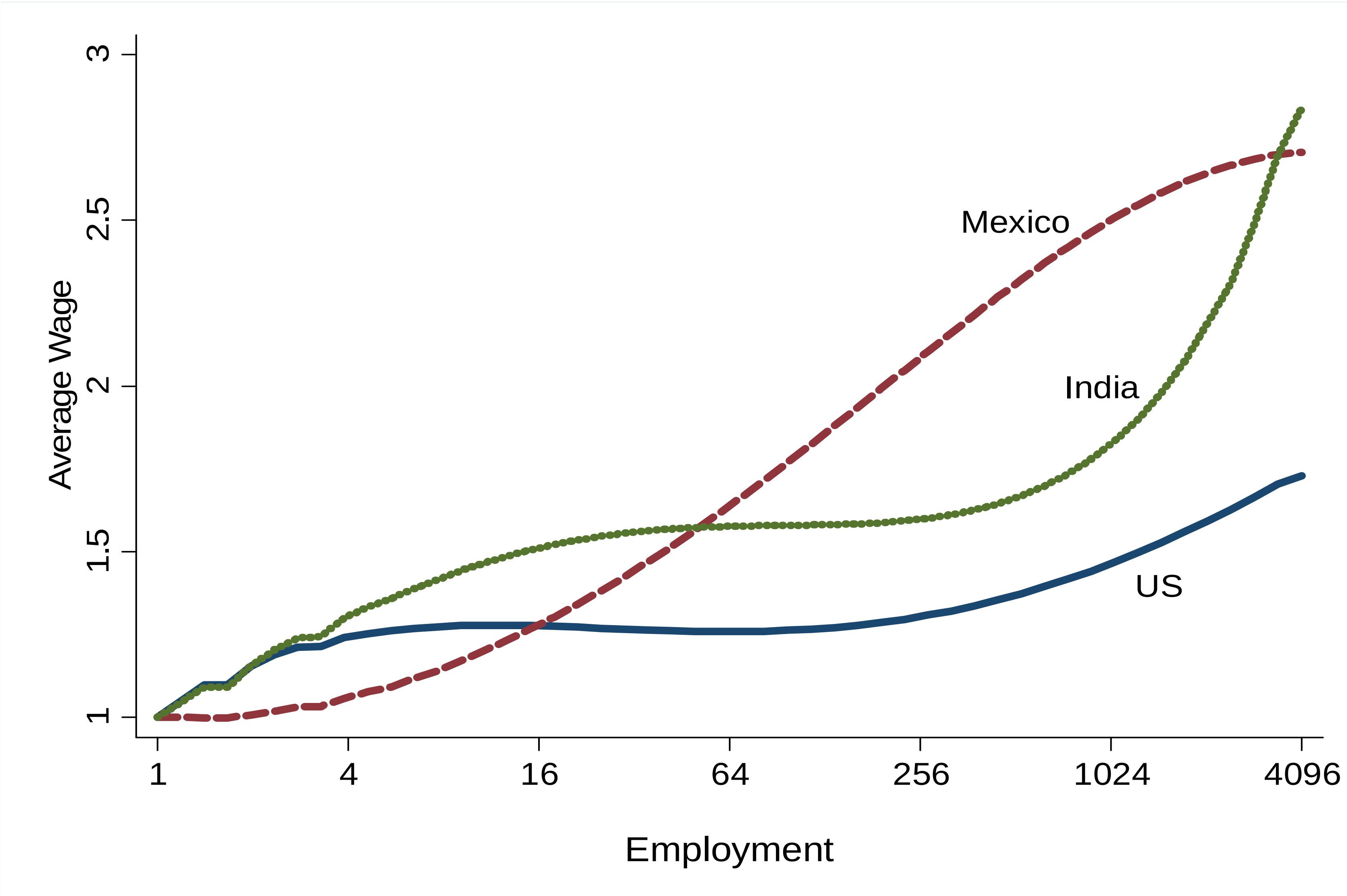
Notes: Average Product growth with age imputed from 1992 and 1997 U.S. Manufacturing Census, 1998 and 2003 Mexican Economic Census, and 1989-1990 and 1994-1995 Indian ASI-NSS.

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



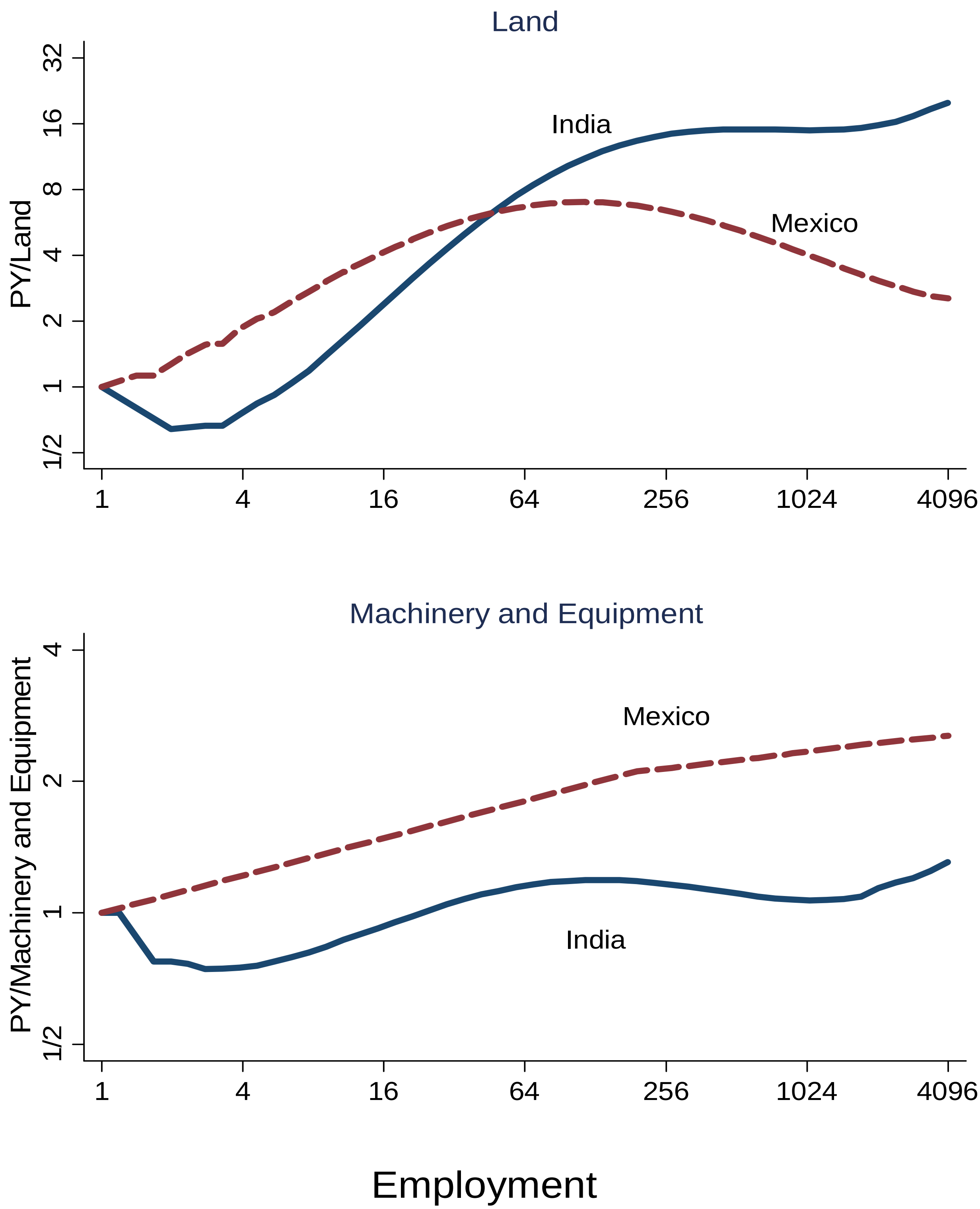
Note: τ and A are relative to weighted average of industry τ and A. Sources: 1994-1995 ASI-NSS (India), 2003 Economic Census (Mexico), and 1992 Manufacturing Census (U.S.).

Figure 9: Average Wage vs. Establishment Size



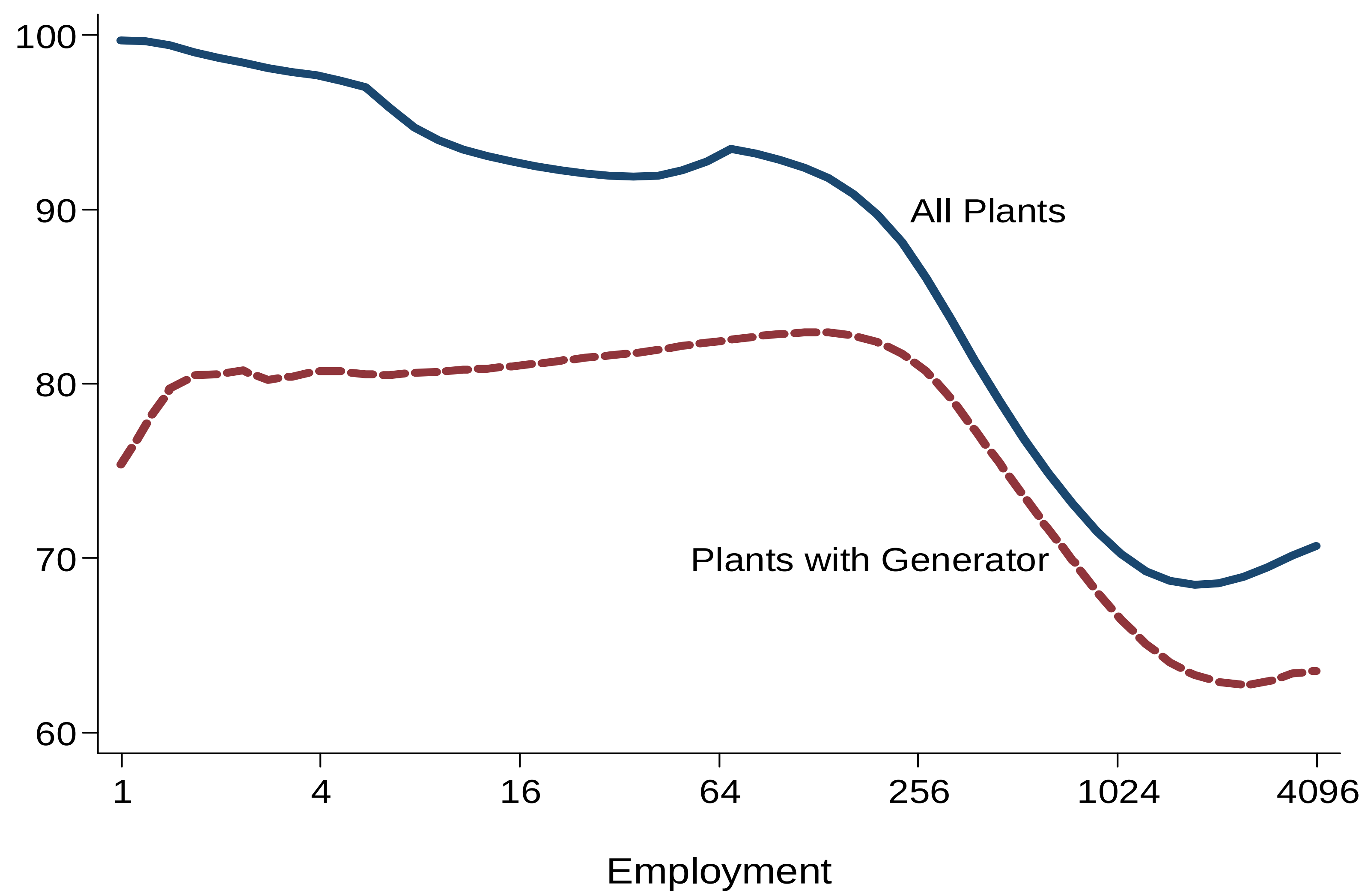
Sources: 1994-1995 ASI-NSS (India), 2003 Economic Census (Mexico), and 2002 Manufacturing Census (U.S.).

Figure 10: Average Productivity of Land and Machinery and Equipment



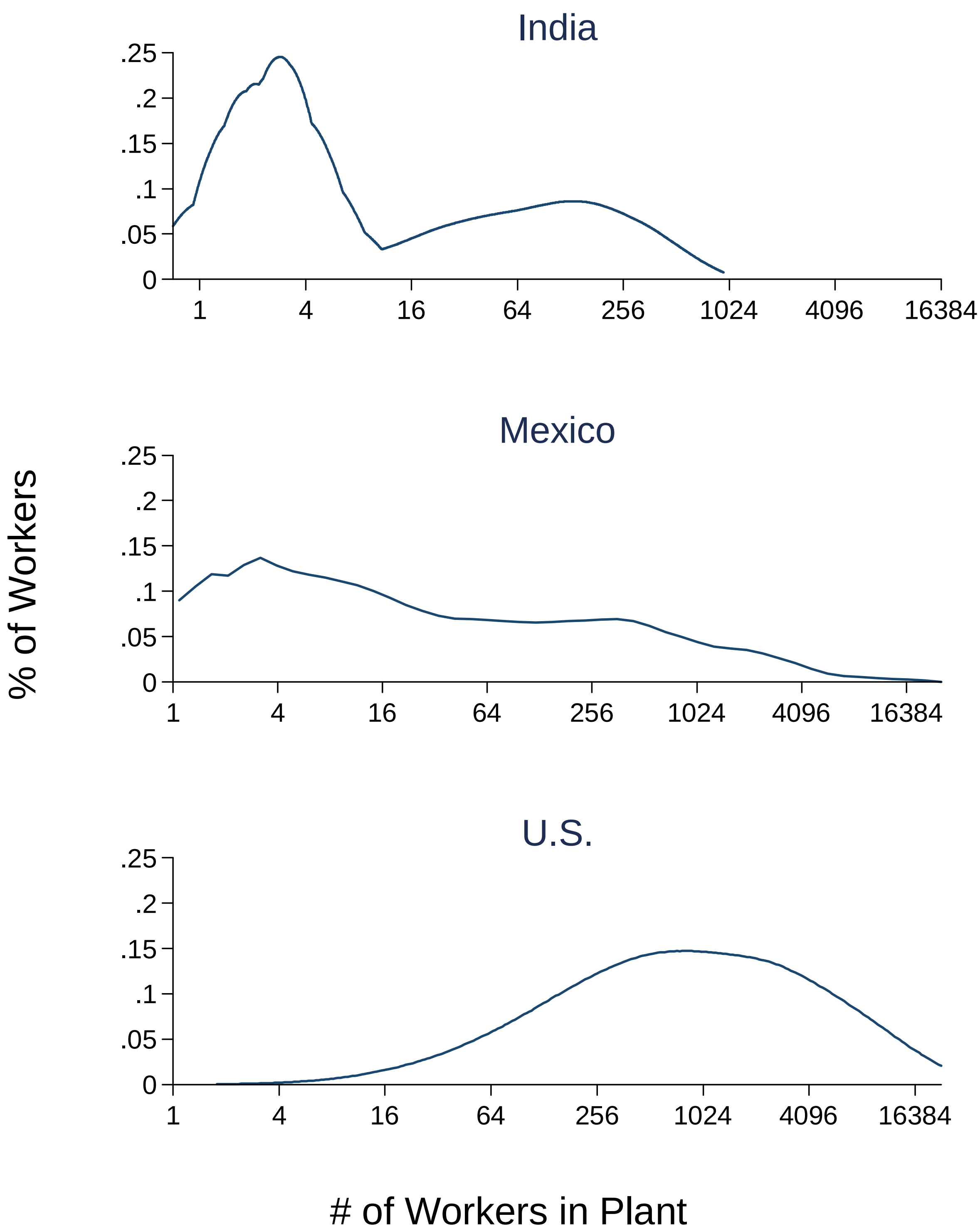
Sources: 1994-1995 ASI-NSS (India) and 2003 Economic Census (Mexico).

Figure 11: % Electricity Purchased from Grid in India



Source: 1994-1995 ASI.

Figure 12: Distribution of Employment by Establishment Size



Sources: 1989-1990 ASI-NSS (India), 2003 Economic Census (Mexico), and 1997 Manufacturing Census (U.S.).

Appendix:

Here we sketch two models that endogenously generate a positive elasticity of average product with respect to underlying 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.

Management Costs

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 *i* 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. (2012) suggest 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 may be less productive in India or Mexico than in the U.S. (a larger value of θ_a) or simply more expensive there relative to lower management layers (higher 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 (e.g. $\theta_w + \theta_a > 0$ and $\mu \geq \sigma$). Importantly for our purposes, the elasticity of n_i with respect to A_i is decreasing in θ_a and θ_w. Correspondingly, the increase in profit from a proportional increase in A_i is lower when θ_a or θ_w are larger.

Average revenue per worker and the average wage at firm *i* are

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

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

The elasticity of average revenue with respect to A_i and the elasticity of the average wage with respect to firm employment are therefore 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* sold 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 to which firm *i* sells. Firm *i* profits from selling in market *j* are

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

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, the number of markets firm *i* sells to is proportional

$$n_i \propto A_i^{\frac{\sigma-1}{\theta}} .$$

The number of markets firm *i* serves is increasing in A_i with an elasticity that is inversely related to how rapidly transportation costs rise with distance (θ). High transportation costs therefore lower the profits from investing in higher A_i.

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