The Life Cycle of Plants in India and Mexico*

Chang-Tai Hsieh
University of Chicago and NBER

Peter J. Klenow
Stanford University, SIEPR and NBER

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Abstract

In the U.S., manufacturing plants grow or die. In contrast, surviving Indian plants exhibit little growth in terms of either employment or output. Indian plants start smaller and stay smaller. Most Indian manufacturing employment is at informal plants with fewer than 10 workers. In the U.S. most workers are at plants with more than 800 workers. Mexico is intermediate to India and the U.S. in these respects. The divergence in plant dynamics could reflect lower investments by Indian and Mexican plants in accessing markets (at home and abroad) and in process efficiency, quality, and variety. 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

In the U.S., older manufacturing plants employ more workers than do younger plants. In the cross-section, forty year old plants are more than six times larger than plants under the age of five. See Figure 1. This relationship between size and age in the U.S. is driven by both market selection and the growth of surviving plants. First, conditional on age, small plants in the U.S. are more likely to die. Second, surviving plants grow in the U.S., as if they invest in new technologies and markets, and produce higher quality and a larger variety of products.

These forces look quite different in India and Mexico. Figure 2 presents the distribution of establishment size in India, Mexico, and the U.S. Figure 3 presents the distribution of employment by establishment size. Not surprisingly, establishments are smaller in India and Mexico than in the U.S. What is perhaps more surprising about India and Mexico is that establishments are born small and remain small forever. Figure 4 presents the cross-sectional relationship between average plant size and age for India and Mexico. In Mexico, plants also start small and double in size by the age of 25, but then stop growing.

The flat employment-age relationship in Mexico and India might arise because more small plants survive in India and Mexico and/or because bigger plants are more likely to die there than in the U.S. The flat employment-age profile may also mean surviving plants in India and Mexico do less investing in technology, access to new markets, or the quality of their products that would enable them to grow. This might be because larger plants face higher taxes or higher labor costs. Levy (2008) argues that payroll taxes in Mexico are more stringently enforced on large plants, discouraging plants from undertaking costly investments. The difficulty of contract enforcement might also make it costly to hire skilled managers that are necessary to grow beyond a certain size. Bloom et. al. (2011) suggest that the most productive textile plants in India do not grow beyond 250 employees because they cannot find the necessary mid-level managers that would allow them to grow beyond this size.

The flat size-age profile in India and Mexico may have an important effect on aggregate productivity and the establishment size distribution. To illustrate this possibility, we use simple GE models of monopolistic competitors with life-cycle productivity based on Melitz (2003) and Atkeson and Burstein (2010). We focus on three mechanisms. First, the productivity of a cross-section of plants is a function of the productivity of young establishments and old stablishments. In turn, the productivity of old establishments is a function of their productivity at birth and their post-entry productivity growth. If post-entry investment in intangible capital is lower in India and Mexico, the productivity of older plants will be correspondingly lower. Second, lower productivity of older plants due to 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 and reduce average establishment size. Third, if potential entrants have some information about their productivity *ex ante*, a larger flow of entrants may bring in marginal entrants who are less productive than infra-marginal entrants. As in Melitz (2003), allowing for selection of entrants implies that more entry is associated with a decline in average entrant productivity. When 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 and a 50% decline in establishment size.

Finally, we show that the lower productivity growth with age in India can be endogenized as in Atkeson and Burstein (2010) as a result of establishment level distortions correlated with productivity and age.

II. Data

To measure the life cycle of manufacturing establishments, we need data that is representative across the age distribution. The typical establishment-level data excludes establishments below a certain size threshold. If young establishments are born small, datasets that exclude most young plants cannot be used to measure the life cycle of plants. We focus on the life cycle in the U.S., Mexico, and India as these are the only countries with establishment level data representative across the age and size distribution.

For the U.S., we use the data from the quinquennial Manufacturing Census. This data is available every five years from 1963 through 2002. The variables we use from the U.S. Census are the wage bill, number of workers, the value-added of the plant, the book value of the capital stock, and the industry (four digit SIC from 1963 to 1997 and six digit NAICS in 2002). The U.S. Census does not provide information on the establishment's age. We impute establishment age based on when the establishment appears in the Census for the first time. We have data every five years starting in 1963 so we group establishments into five-year age groupings. The number of establishments in the U.S. Manufacturing Census is about 300 to 350 thousand.

For India, we combine the data from a survey of formal manufacturing plants (the Annual Survey of Industries) and a separate survey of informal plants (Schedule 2 of the Indian National Sample Survey). We have these two datasets for four years: 1989, 1994, 1999, and 2004. The survey of informal establishments is conducted every five years as one of the modules (schedule 2) of the Indian National Sample Survey. The survey of informal plants only provides data on establishment age in 1989 and 1994, so when measuring the life cycle we restrict our attention to these two years. The Survey of formal establishments (ASI) is a census of manufacturing establishments with more than 100 employees and one-third sample of formal establishments with less than 100 employees.

To make the Indian data comparable to the U.S., we restrict the sample to sectors that are also classified as manufacturing in the U.S. data.[1] The key variables we use are number of workers, the wage bill (for the establishments with paid employees), the book value of the capital stock, value added, industry (at the four digit level), and establishment age. Establishment age is available for all years in the data on formal plants, but only available in 1989 and 1994 in the data on informal plants.

Table 1 presents the sample sizes in the two datasets (columns 1 and 2) and the aggregate number of establishments (columns 3 and 4) computed from the sampling weights. In 1994, there were 107 thousand formal manufacturing establishments and more than 12 million informal establishments. Table 2 presents the number of workers in the two types of establishments. In 1994, 7.9 million workers were employed in formal manufacturing establishments and 20.6 million workers were employed in the informal manufacturing sector.[2] Interestingly, the share of the informal sector, both in the number of establishments and number of workers, increased from 1989 to 2004. Also, note the significant difference in the share of unpaid workers between the

[1] 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.

[2] We checked that the total number of workers shown in Table 2 (from establishment level data) is roughly consistent with the estimates of total manufacturing employment from the labor force module (Schedule 10) of the National Sample Survey. For example, the total number of manufacturing workers in the labor force survey (Schedule 10) was 35.7 million in 1999 and 46 million in 2004. The corresponding numbers in the establishment level data (shown in Table 2) are 37 million in 1999 and 45 million in 2004.

formal and informal plants.[3] Workers in formal plants are overwhelmingly paid employees. In informal establishments, paid employees are a minority, accounting for 10 percent of the labor force in 1989 and 1994. In 1999 and 2004, the share of paid employees in the informal plants increased to more than 20 percent. Table 3 provides the share of unpaid workers by sector. The fraction is over one-third in 12 of the 19 industries, so the phenomenon is not confined to just a few activities.

For Mexico, we use data from the Mexican Economic Census. The Economic Census is conducted every five years by the 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 captured in the Economic Census are street vendors, public sector entities, and establishments in the agricultural sector. To make the data comparable to the U.S., we restrict our attention to establishments in the manufacturing sector.[4] We have access to the Mexican Censuses from 1998, 2003, and 2008. The variables we use from this data are the number of workers, the wage bill, book value of the capital stock, value-added, establishment age, and industry (at the six digit level).

Table 4 presents the summary statistics of the Mexican data. The number of establishments in the Mexican data increased from 344,000 in 1998 to 437,000 in 2008. The share of employment in family firms is lower than in India, but note that the share of unpaid workers increased from 1998 to 2008. The Table also presents an estimate of the number of paid workers paying social security taxes (IMSS). Although paid workers are legally obligated to pay 18% of the wage bill as social security taxes, there is widespread evasion of this tax (Levy, 2008). We estimate the number of formal paid workers as the ratio of social security payments/wage bill in the Census to the tax rate (18%). Less than a quarter of paid workers are in compliance with this tax, and the compliance rate has declined from 1998 to 2008.

[3] The 1999 ASI does not provide information on unpaid workers. The share of unpaid workers in total employment in the ASI plants is 1.5 percent in 1989 and 1994 and 0.8 percent in 2004 (the ASI has information on unpaid workers in 1989, 1994, and 2004).

[4] 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.

III. The Life Cycle of Manufacturing Plants

We begin by presenting evidence from the cross-section on the relationship between plant size and age. We control for four digit industries so all the facts we show in this section 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 the summary statistics on the size of establishments in India and Mexico. Table 5 presents the summary statistics on the distribution of establishment size (Figure 2 is the corresponding plot). The median establishment employs 3 workers in India, 7 workers in Mexico, and 48 workers in the U.S. The corresponding size of the establishment in the 75th percentile of the size distribution is 9 workers in India, 17 workers in Mexico, and 152 workers in the U.S. Table 6 presents the distribution of *employment* by establishment size (Figure 3 is the corresponding plot). The median worker is employed in an establishment with 5 workers in India, 24 workers in Mexico, and almost 900 workers in the U.S. The corresponding numbers at the 75th percentile are 57 workers in India, 55 workers in Mexico, and almost 2,800 workers in the U.S.

Figure 4 illustrates the flat relationship between plant size and age in the Indian cross-section. In India, establishments are small because they are born small and stay small forever. Mexico is an intermediate case: the relationship between size and age is positive from age 0 to age 25 but is flat after age 25. Figure 5 provides similar evidence, this time showing the cross-sectional relationship between plant revenue (value-added) and age in the cross-section. Measured by establishment revenue, older Mexican plants (above age 30) are almost three times larger than younger plants (less than age 5). This is larger than the gap between young and old establishments when size is measured by employment, but still significantly smaller than the size gap between young and old establishments in the U.S. (a factor of 7.4 in the cross-section). In India, average output of establishments more than 39 years old is more than 30 percent *lower* than that of establishments under 5 years of age.

It might not be so surprising that size is not increasing in age for informal Indian plants, as they may stay small precisely to avoid costs of formality (taxes, regulations). The World Bank (2010) ranks India 163rd out of 183 countries for ease of starting a formal business, and

164th for costs of complying with the tax code. Figure 6, however, shows that the size-age relationship is also fairly flat for *formal* Indian plants in both 1989 and 2004.

Figure 7 presents the distribution of employment by establishment age. The employment distribution by establishment age is a function of the size-age relationship (Figure 4), the size of each cohort at birth, and the exit probability with age (Figure 8). The bottom panel of Figure 7 presents the distribution for the U.S. As is well known (e.g., Atkeson and Kehoe, 2005), much employment in the U.S. is concentrated in older plants. Establishments more than 39 years old account for almost 30 percent of total employment while plants younger than 10 account for slightly over 20 percent of total employment. In India and Mexico, older plants (older than 39 years) account for less than 10 percent of employment, while establishments less than 10 years old account for almost 50 percent of total employment.

Table 7 presents regressions of log plant employment on plant age industry by industry in the U.S. and India. The difference is pervasive. In 17 out of 19 two industries in the U.S., employment increases about 5% a year with age in the cross-section. In 17 out of 19 industries in India, employment rises at 1% or (usually) less.

We have so far presented the relationship between size and age in the cross-section. This conflates size differences between cohorts at birth and the employment growth of a cohort over its life cycle. Ideally, to measure the life cycle, we want to follow a cohort over its entire life cycle (say 40 years). We have the data to do this for the U.S. but we are limited in what we can do for India, where we have data on establishment age for 1989 and 1994, and Mexico, where we have data for 1998, 2003, and 2008. The shortcut we take is the following. In India, we start with the 1989 cross-section. We then compare establishments of a given cohort in 1989 with the same cohort five years later in 1994. For example, we compare the size of plants less than five years of age in 1989 with plants between the ages of 5 and 9 in 1994. We do this for all the cohorts defined in five year groups. The growth rate for each five year cohort at different stages of their life cycle is an accurate estimate of a cohort's life cycle if life-cycle growth is the same for every cohort. We do the same thing for Mexico by comparing 1998 to 2003 and for the U.S. by measuring the change from 1992 to 1997 for all the five year groupings of cohorts.

The resulting estimates of the change in plant employment over the five years are shown in Figure 9. A comparison of Figure 9 with the cross-sectional evidence in Figure 4 indicates that the cross-section gives a slightly biased picture of the life cycle. In India, under the assumption that life-cycle growth is the same for all cohorts, the over-time evidence suggests that plant employment falls by almost 1 log point from age < 5 to age > 35, whereas the cross-section indicates a much smaller decline. In Mexico, the comparison of cohorts over time indicates that plant employment grows by 65 percent from age < 5 to age > 35 whereas the cross-section suggest almost a doubling in plant size. In contrast, the cross-section for the U.S. provides a downwardly biased estimate of the growth of plant size with age. Under the assumption that growth with age is the same for all cohorts, the estimate of the life cycle obtained from following cohorts from 1992 to 1997 suggests that establishments increase by roughly a factor of nine (instead of a factor of six suggested by the cross-section) from birth to age > 35.[5]

One reason for life-cycle growth to differ between cohorts is if there are aggregate shocks that hit cohorts differentially. One might worry, for example, that the five year periods for which we have data for India and Mexico might be low growth periods and thus the flat size-age life-cycle profiles might simply reflect this. Figure 10 plots log aggregate output per worker in manufacturing in India and Mexico to assess this possibility, where the vertical lines are drawn over the five year periods that our micro-data is drawn from. The figure indicates that 1989-1994 is not an exceptionally low growth period in India, and 1998-2003 are not low growth years in Mexico.

Growth in average employment of a cohort can be driven by growth of survivors and by the exit of small establishments. Figure 11 presents evidence of the importance of these two forces for the U.S. It shows growth of all establishments (as in Figure 9) along with the growth of surviving establishments. Survivor growth is lower than overall growth, suggesting that exit in the U.S. is negatively correlated with size. Surviving establishments, however, also experience substantial growth. Both forces – the exit of small plants and the growth of surviving plants – play important roles in the life-cycle growth of a cohort of establishments.

We do not have panel data in India and Mexico as we do in the U.S., so we cannot directly assess the importance of selection vs. survivor growth in India and Mexico. As indirect evidence of the importance of selection, Figure 12 plots life-cycle growth of the log of average

[5] In the U.S., where we can measure the life-cycle correctly by following cohorts over forty years, we obtain estimates very similar to Figure 9 based on growth from 1992 to 1997.

employment vs. the average of log employment.[6] We normalize the under 5 age group to zero. The growing gap between the log of average employment and the average of log employment with age can be interpreted as the change in the dispersion of log employment. For the U.S., the growth of mean log employment is faster than the growth of log mean employment, suggesting that dispersion of log employment falls over the life cycle. If the employment dispersion of surviving plants is unchanged over the life cycle, the falling dispersion of employment is consistent with the exit of the smallest establishments. The evidence from Indian establishments also suggests falling employment dispersion, but by much less than in the U.S. In Mexico, the dispersion of log employment appears to widen with age.

Figure 12 does not provide definitive evidence on the importance of selection in Mexico and India relative to the U.S. because the dispersion of surviving plants could be changing with age in the U.S. relative to India and Mexico. If this is not the case, however, then the evidence in Figure 12 indicates that selection is less negatively correlated with size in India and Mexico than in the U.S. If selection does not lead to the exit of low productivity plants in India and Mexico, this would partially explain why the growth rate of average establishment size with age is low in these two countries.

Productivity over the life cycle

We now impose more structure on the data in an attempt to back out the life cycle of establishment productivity. Consider a closed economy version of Melitz (2003). Suppose that aggregate output at time *t* is given by the following CES aggregate of the output of individual establishments:

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

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[6] Ideally we would like to directly show the dispersion of plant employment over the life-cycle of a cohort. We have this statistic for India and Mexico but not for the U.S. (we plan to calculate this statistic when we next have access to the U.S. Census micro-data).

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

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

where $P_{a,i}$ is the plant-specific output price, $L_{a,i}$ is the plant's labor input (measured as its wage bill relative to a common wage w), $K_{a,i}$ is the plant's capital stock, and R is the common, undistorted rental cost of capital. Here $1-\tau_{Y_{a,i}}$ denotes an establishment-specific distortion that affects the private value of the marginal product of capital and labor equally, and $1+\tau_{K_{a,i}}$ denotes a distortion that affects the private value of the marginal product of capital *relative* to that of labor. Such wedges might arise for any number of reasons, such as taxes, markups, adjustment costs, transportation costs, size restrictions, labor regulations, and financial frictions.[7]

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

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

where $A_{a,i}$ is plant-specific productivity , or *TFPQ* in the terminology of Foster, Haltiwanger and Syverson (2008). 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 of the plant is then proportional to

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

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

where $TFPR_{a,i} \propto \frac{\left(1+\tau_{K_{a,i}}\right)^{\alpha}}{1-\tau_{Y_{a,i}}}$ is a weighted average of the marginal products of capital and labor. See Hsieh and Klenow (2009) for additional details. Here we are building on the distinction Foster, Haltiwanger and Syverson (2008) make between "revenue" TFP (TFPR) and "quantity" TFP (TFPQ, which is equivalent to $A_{a,i}$ here).

As shown in (1.4), a plant's revenue is increasing in its productivity (TFPQ) and decreasing in the value of its marginal products (TFPR). More productive plants have lower costs and therefore charge lower prices and reap more revenue (given $\sigma > 1$), holding fixed TFPR. Plants with higher TFPR charge higher prices and earn less revenue, for a given TFPQ. More to the point of our analysis here, the *growth* of plant revenue 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 marginal products change with age.

In this framework, aggregate output can be expressed as

$$(1.5) \qquad Y = \underbrace{\left[\sum_a \sum_{i=1}^{N_a} \left(A_{a,i} \cdot \frac{\overline{TFPR}}{TFPR_{a,i}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}}}_{TFP} K^{\alpha} L^{1-\alpha}$$

where K and L are sums of capital and labor across all plants. $\overline{TFPR}$ is the inverse of revenue-share-weighted average inverse plant TFPR.[8]

As emphasized in Hsieh and Klenow (2009), cross-plant dispersion in TFPR around $\overline{TFPR}$ lowers aggregate TFP. But our focus here is on the life cycle behavior of TFPQ. So, for simplicity, suppose TFPR does not vary within an age cohort. Then aggregate TFP simplifies to a weighted average of the "representative" TFPQ in each cohort:

$$(1.6) \qquad TFP = \left[\sum_a N_a \left(A_a \cdot \frac{\overline{TFPR}}{TFPR_a} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}}$$

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[8] $$\overline{TFPR} \equiv \frac{\sigma}{\sigma-1} \left[\frac{R}{\left(\alpha \sum_a \sum_{i=1}^{N_a} \frac{1-\tau_{Ya,i}}{1+\tau_{Ka,i}} \frac{P_{a,i}Y_{a,i}}{PY} \right)} \right]^{\alpha} \left[\frac{w}{\left((1-\alpha) \sum_a \sum_{i=1}^{N_a} (1-\tau_{Ya,i}) \frac{P_{a,i}Y_{a,i}}{PY} \right)} \right]^{1-\alpha}$$

where a cohort's representative TFPQ is

(1.7) $$A_a \equiv \left(\sum_{i=1}^{N_a} A_{a,i}^{\ \sigma-1} \Big/ N_a \right)^{\frac{1}{\sigma-1}} .$$

Figure 13 plots the growth of representative productivity over the life cycle of the plant.[9] The top panel, for India, indicates that plant productivity does in fact grow with age, by 35 percent from birth to age > 35. The reason why growing productivity does not translate into growing size in India is that the marginal products of capital and labor (as summarized by TFPR) are also growing with age. Older Indian establishments are smaller than they would be in an economy where marginal products were equalized across plants by age. In Mexico, plant productivity increases by 65 percent from age < 5 to age < 10 (and greater than 4). The rise in plant employment (Figure 8) is slightly smaller, again because marginal products for Mexican plants also increase over this age range. In the U.S., average productivity increases by a factor of *nine* from birth to age > 35. The productivity increase with age in the U.S. is about the same as the increase in establishment size.

We end this section with two sets of robustness checks. Figure 14 presents the employment share by age using U.S. output shares for each sector to aggregate the employment shares for each sector into an aggregate employment share. The dark bars are the employment shares computed with Indian or Mexican sectoral output shares (already shown in Figure 7); the light bars represent the employment shares computed with U.S. sectoral output shares. Figure 15 presents the distribution of establishment by size when the distribution for each sector is aggregated using U.S. output shares for each sector. The dashed line represents the size distribution aggregated with U.S. output shares and the solid line the distribution aggregated with Indian or Mexican output shares. As can be seen, the employment distribution by age and the distribution of establishments by size are little affected by using U.S. output shares to aggregate the industry level statistics.

Our analysis for India has so far been limited to 1989 and 1994, as these are the only two years for which the survey of informal plants (from the NSS) provides information on the establishment's age. A natural question is whether the facts look different in India now, after

[9] This is actually life cycle TFPQ growth *relative* to the TFPQ growth of entering cohorts, as the TFPQ of the youngest cohort is normalized to 1 in each year.

almost twenty years of economic reform. We cannot look at whether the life cycle has changed in India, but we can look at whether the size distribution of plants has changed. Figure 16 presents the distribution of employment by size for 1989 and 2004 in India. There is evidence of a thicker mass of plants employing 4 to 16 workers and fewer plants with more than 16 workers in 2004 than 1989. But the size of the median establishment is unchanged at 3 workers.

IV. 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.[10] We do this for a sequence of simple GE models built around monopolistic competitors with life cycle productivity. In addition to Melitz (2003), many of our modeling choices follow Atkeson and Burstein (2010).

For all of the models we assume:

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

These assumptions imply two convenient properties about the resulting equilibria:

(g) a stationary distribution of plant size in terms of labor
(h) 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).

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

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

(1.8)
$$TFP = \frac{Y}{L} = \left[\sum_a \sum_{i=1}^{N_a} \left(A_{a,i} \cdot \frac{\overline{TFPR}}{TFPR_{a,i}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}} \frac{L_Y}{L}$$

where $Y_{a,i} = A_{a,i} L_{a,i}$ and $TFPR_{a,i} \equiv \frac{P_{a,i} Y_{a,i}}{L_{a,i}} = P_{a,i} A_{a,i} = \frac{1}{1-\tau_{a,i}}$. As these models do not have capital, we assume a single revenue distortion $\tau_{a,i}$ hitting each plant.[11]

In (1.8), 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 TFPQ varies only by age. All entrants have the same TFPQ, and it grows exogenously with age. Exit rates depend on age only. All plants have the same TFPR. In this case we simply get

(1.9)
$$TFP = \left[\sum_a N_a A_a^{\sigma-1} \right]^{\frac{1}{\sigma-1}}.$$

Implicit in (1.9) is allocation of labor to exploit variation in TFPQ across cohorts. We calculate aggregate TFP in this way with U.S. representative TFPQ by age and, separately, *with Indian representative TFPQ by age*. We normalize the mass of entrants to $N_1 = 1$, and keep the exit

[11] Here $\overline{TFPR} \equiv \frac{\sigma}{\sigma-1} \frac{w}{\sum_a \sum_{i=1}^{N_a} \frac{P_{a,i} Y_{a,i}}{PY} (1-\tau_{a,i})}$.

rates by age at U.S. levels displayed in Figure 8.[12] Table 8 lists the parameter values chosen for this model and subsequent models.

The first column of Table 9 reports that, in this simplest GE model, going from U.S. to Indian life cycle TFPQ 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 directly 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. Holding entry and exit fixed, the pace of exogenous life cycle growth has *zero* impact on average employment per plant. In this version of the model, plants do not start small and stay small, but rather start medium-sized and stay so. To help explain the size distribution in India vs. the U.S., life cycle growth would need to boost entry (and/or slow exit).

In a Melitz-style model with endogenous incumbent innovation, Atkeson and Burstein (2010) show that lower TFPQ growth of incumbents can indeed 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 offset the costs of lower average TFPQ.[13]

The second column in Table 9 shows what happens when we allow for endogenous entry when moving from U.S. to Indian life cycle growth. Average TFPQ 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 TFPQ growth is not the whole story behind life cycle employment growth in India than the U.S. TFPR increases with age in India, whereas it falls with age in the U.S. We

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

[13] One can re-write (1.9) 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 TFPQ term.

next add this variation to the model in the form of age-specific taxes and transfers – a reduced form for not just tax rates but size restrictions, labor regulations, financing costs, and so on. The penultimate column of Table 9 shows that this distortion has a modest effect on aggregate TFP with fixed entry. Whereas moving from U.S. to Indian TFPQ by age lowers aggregate TFP by 24.4%, moving from U.S. to Indian TFPR by age at the same time lowers productivity 25.7%. The final column of Table 9 adds back free entry to this scenario. The steeper TFPR by age in India galvanizes entry (now up 49%, vs. 17% with only TFPQ by age). Discounted profits rise even more if older plants are restrained (in terms of TFPR) as well as growing slowly in terms of TFPQ. 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% with free entry and only TFPQ changing with age). Fattal Jaef (2011) obtained a similar variety offset when considering the costs of rising TFPR with age in a closely related model.

A few comments about the variety offset deserve mention here. First, the model assumes a linear entry technology. Doubling entry of the same quality (TFPQ) 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 TFPQ and/or TFPR. 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. Third, the strength of the variety offset may be sensitive to the way we are modeling rising TFPR with age. If rising TFPR reflects rising tax rates with age, then steeper TFPR with age lowers future profits and raises near-term profits for entrants. But suppose rising TFPR with age is partially due to, say, rising markups with age. Without modeling the sources of markup variation in India vs. the U.S., it's not clear how this would affect entry.

Another missing ingredient from the Table 9 models is TFPQ dispersion within age cohorts. So now suppose, as in Melitz (2003), entrants are homogenous *ex ante* (drawing from the same log normal distribution of initial TFPQ) and heterogeneous *ex post* (based on realizations of the TFPQ draws). We start with fixed entry. In this environment, the effects of going from U.S. to Indian life cycle TFPQ are similar to those in the first two columns of Table 9, which feature no TFPR dispersion and TFPR dispersion only by age, respectively. So TFPQ dispersion within cohorts, by itself, does not amplify or diminish the losses from slow life cycle TFPQ growth. The same is true if we allow TFPR to differ by TFPQ within age groups in a common way. In the U.S. the elasticity of TFPR with respect to TFPQ is 0.13. Perhaps not surprisingly, this too has little effect on the productivity drop going from U.S. to Indian life cycle TFPQ and TFPR.

In Table 10 we consider richer models in which there is not only TFPQ and TFPR dispersion within cohorts, but also a different slope of TFPR with respect to TFPQ between the U.S. baseline and the Indian alternative. In India, the slope of TFPR with respect to TFPQ is much steeper at 0.56.[14] 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 TFPQ by age *and* TFPR by both age and TFPQ results in 54.5% lower aggregate TFP when entry is fixed. This figure is so much higher because of the static misallocation created by greater TFPR dispersion across plants with different TFPQ levels in India.[15] In the second column of Table 10 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 TFPR with respect to TFPQ in India results in a weaker variety offset.

So far we have set the standard deviation of the log normal distribution of initial entrant TFPQ to match the U.S. data. But TFPQ is more dispersed for young plants in India than in the U.S. The standard deviation of log TFPQ is 1.25 in India vs. 1.01 in the U.S. for plants age 0-4. Greater entrant TFPQ 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 TFPQ *ex ante*. Instead of a free entry condition, wherein expected profits are zero for all entrants, there is a marginal TFPQ entrant with zero discounted

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[14] If TFPR increases too rapidly with TFPQ, then plant employment is actually decreasing in plant TFPQ. 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 TFPQ in India.

[15] 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. TFPR dispersion, including TFPR dispersion that did not relate to either TFPQ or age. And we held fixed the distribution of TFPQ in our calculation.

profits. All those with initial TFPQ above the zero-profit threshold enter and earn positive discounted profits. The penultimate column of Table 10 considers this case. We calibrated the mass of potential entrants so that we can match the TFPQ dispersion in India when we go from U.S. TFPQ and TFPR to Indian TFPQ and TFPR. 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. Representative TFPQ of entrants *falls* by 49%, whereas it was previously fixed. This helps drag down representative TFPQ of all plants by 65%. But variety is up 62%. Entry labor is now quite small to explain why the low TFPQ marginal entrant has zero profits, so the surge of entry in the "Indian" counterfactual does not require much labor.

The final column in Table 10 endogenizes incumbent TFPQ growth *a la* Atkeson and Burstein (2010).[16] Incumbents choose the probability q of taking a step up vs. down in proportional TFPQ 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 cost of this investment for a plant is

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

In this formulation, it is exponentially more costly for higher TFPQ plants to boost their TFPQ 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 TFPQ by age in the U.S. We then gauge the effect of moving from the joint distribution of TFPR with TFPQ and age in the U.S. to the distribution of TFPR with TFPQ and age in India. The steeper slope of TFPR with respect to TFPQ in India discourages incumbent innovation in the same way that trade barriers do in Atkeson and Burstein's analysis. The result is 55% lower TFPQ of the average

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

plant.[17] As entrants have less competition from incumbents, entry rises 74%. We think this large increase is fueled by reallocation of labor from incumbent innovation to entry. The share of the population working falls 9%, less than the 12% under exogenous innovation precisely 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.

In Table 11 we collect the implications for average plant size in each model with endogenous entry. We measure plant size in the model by production employment (i.e., excluding labor devoted to entry and innovation). The first column shows the data for the U.S. in 2002 and India in 1994: 197 workers per plant in the U.S. vs. 18 in India.[18] So plants are an order of magnitude larger in the U.S. than India. In each model, the fixed entry cost (in terms of labor) is chosen to match the average plant size in the U.S. – as shown redundantly in the table. The models predict workers per plant between 102 and 160 for India. The minimum of 102 is in the model with incumbent innovation, where R&D labor is freed up to finance more entry in response to steeply rising TFPR with TFPQ in the India. Clearly, the models have limited success in explaining the much smaller average size of plants in India than in the U.S.

V. Conclusion

In contrast to the U.S., where manufacturing plants grow with age, manufacturing plants in Mexico and India exhibit little growth in terms of employment or output. We show that lower life-cycle growth in Mexico and India can have important effects on aggregate TFP and on the plant size distribution. We highlight three main effects. First, holding fixed the number and productivity of entrants, lower productivity growth with age makes incumbents less productive and thus lowers aggregate TFP. Second, lower incumbent productivity reduces the competition faced by entrants. If we allow the flow of entrants to respond, lower life-cycle growth can induce more entry and help explain the smaller average plant size observed in India and Mexico.

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[17] As with the variety offset, a "TFPR explanation" may be sensitive to the exact source of rising TFPR with respect to TFPQ in India. We have modeled it as rising tax rates. Rising markups, for example, might have ambiguous incentives for incumbent innovation.

[18] Here we simply divide total employment by the number of plants. Hence the numbers differ from the median establishment's employment in Table 4 and from the median worker's establishment employment in Table 5.

Third, if we allow potential entrants to observe their productivity *ex ante*, a larger flow of entrants may invite marginal entrants who are less productive than the infra-marginal entrants. The result can be a bigger drop in aggregate productivity and wider dispersion in entrant productivity. When moving from the U.S. life cycle to the Indian life cycle, the net effect of these three forces can plausibly produce a 25% drop in aggregate TFP and a 50% decline in establishment size.

We emphasize that our analysis is very much a first pass at modeling the aggregate effect of differences in the life cycle. A richer model could allow for complementarities between worker skill and plant size, which might account for the bulk of the difference in the size distributions. Explicitly modeling how financial and other contractual frictions affect the life cycle would also be useful. Allowing for market access costs as in Arkolakis (2010) and Li (2011), meanwhile, could produce more realistic estimates of the welfare gains from greater entry in India and Mexico. Finally, it might be useful to endogenize exit rates. This would allow one to determine the extent to which differences the distribution of productivity (TFPQ) and marginal products (TFPR) over the life cycle can explain differences in the selection mechanism.[19]

An important question we hope to address in the future is *why* the life cycle looks so different in India and Mexico. Why exactly do TFPQ and TFPR evolve differently as plants age in India and Mexico compared to the U.S.? Some candidate explanations are higher tax rates and tax compliance costs with size, and transportation costs that presumably affect high productivity plants more. In addition, the fact that so much Indian employment consists of unpaid (family?) labor suggests that labor contracting frictions might also be an important force.

[19] The World Bank (2010) ranks India 134th out of 183 countries for ease of *closing* a business.

Figure 1: Plant Size by Age in the U.S. Cross-Section (2002)

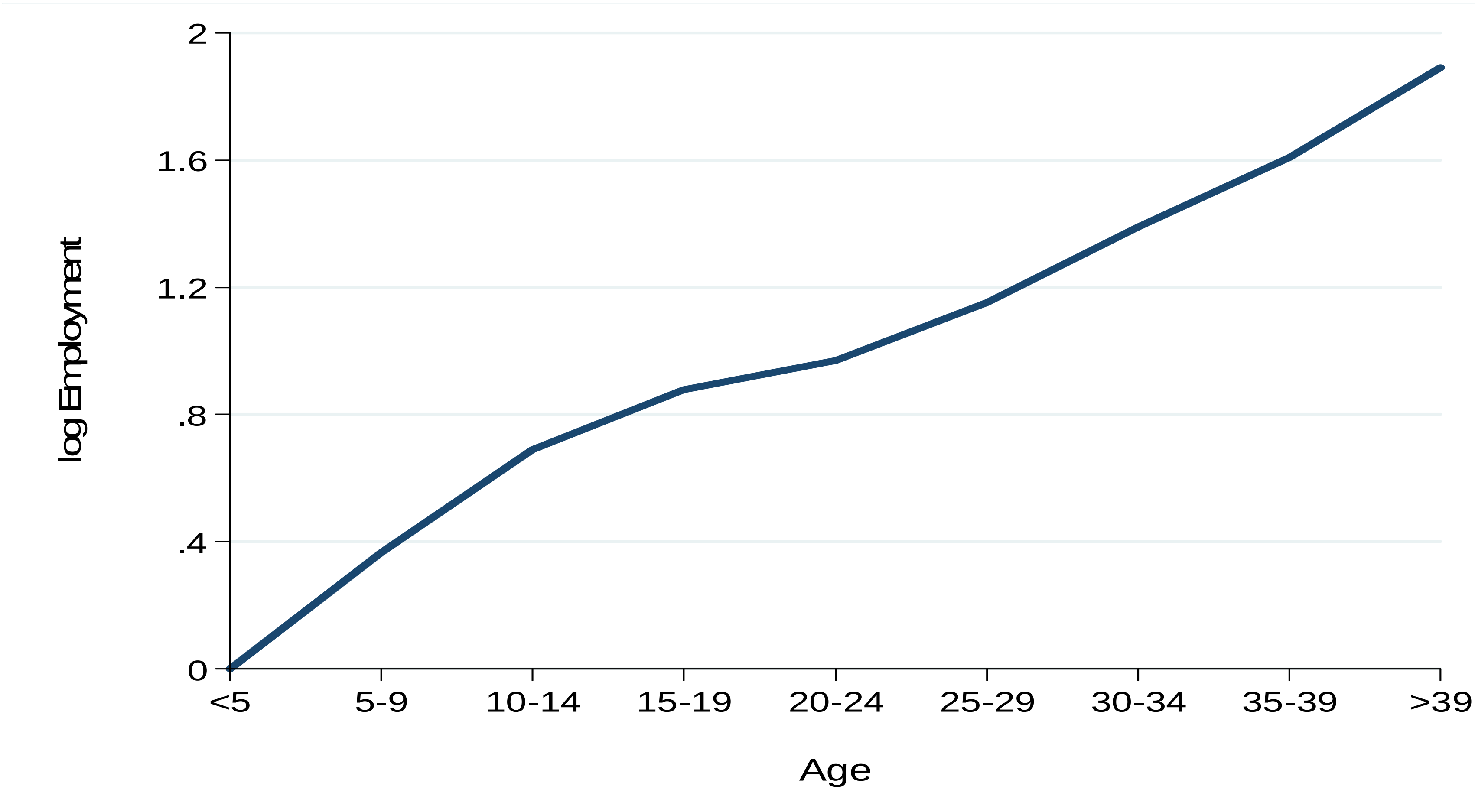

Figure 2: Density of Establishments by Size

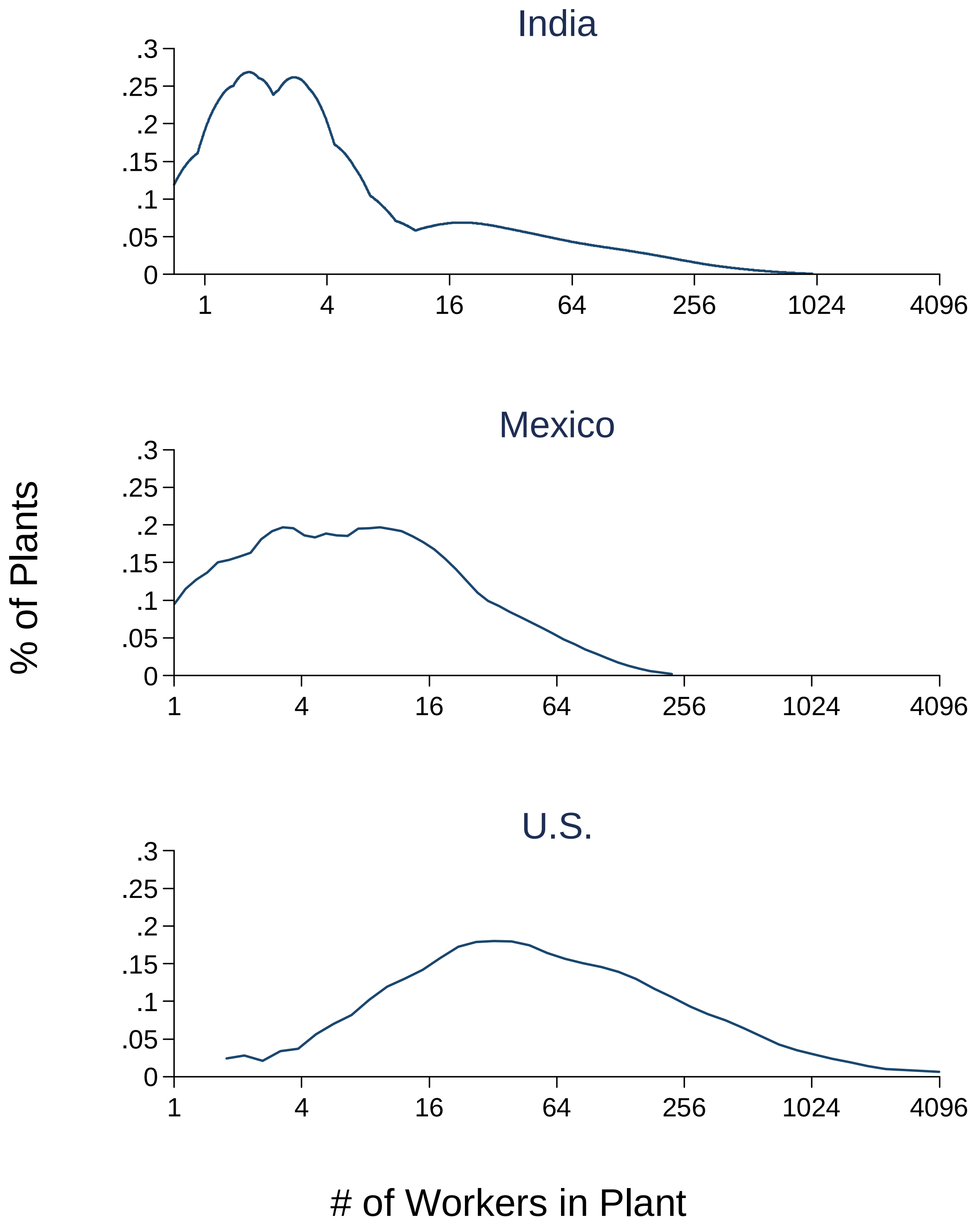

Figure 3: Density of Employment by Size

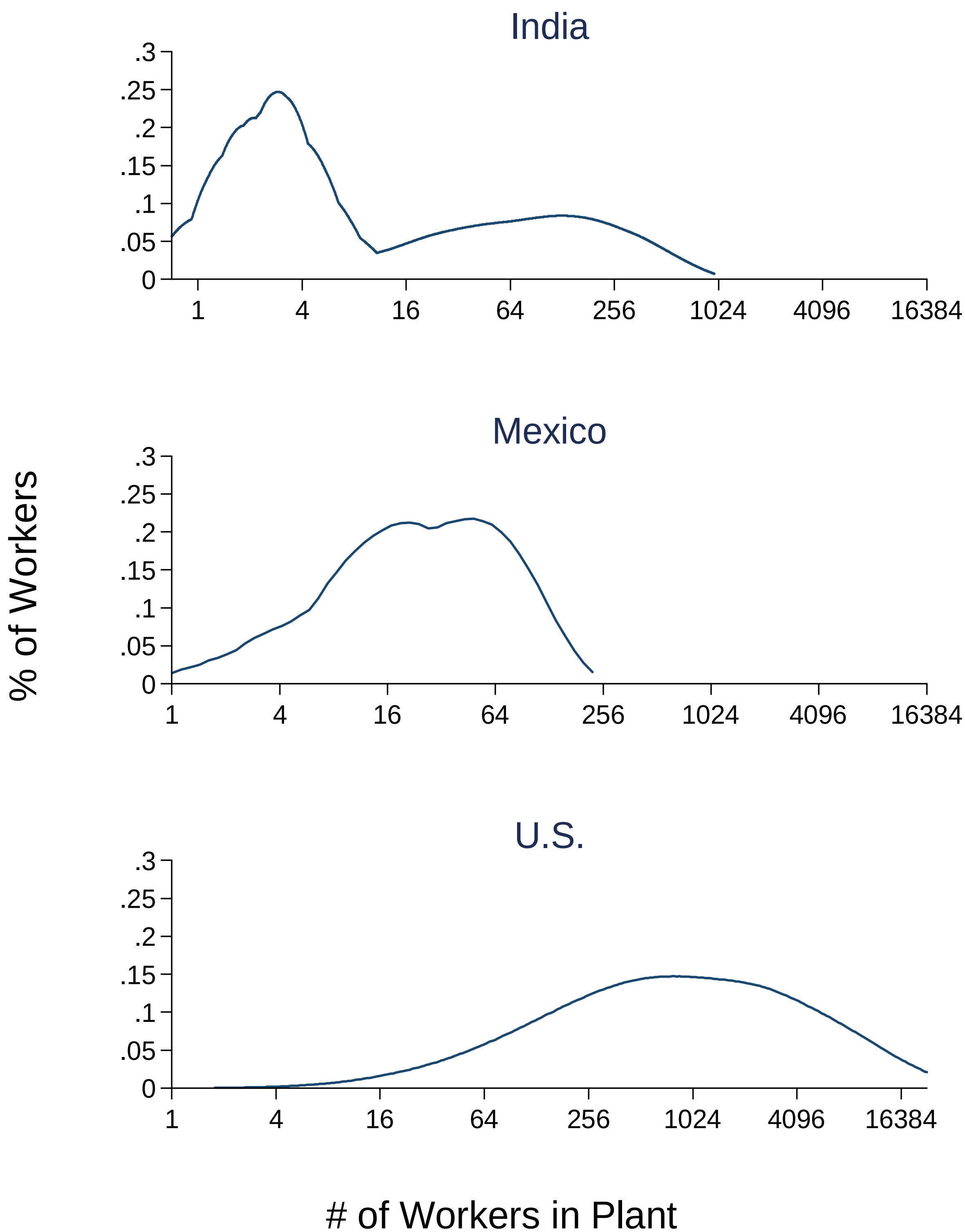

Figure 4:
Plant Employment by Age in the Cross-Section

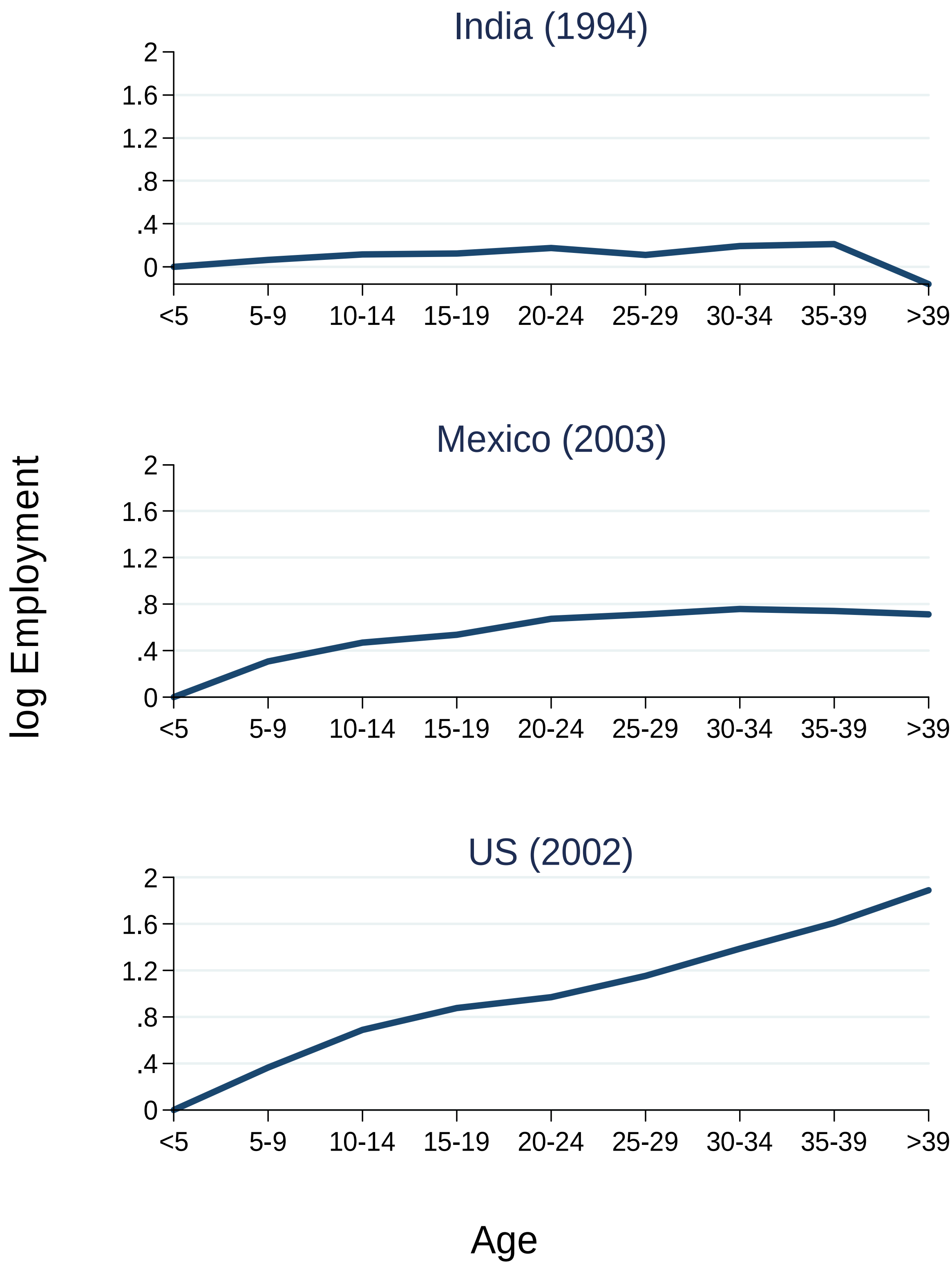

Figure 5:
Plant Output by Age in the Cross-Section

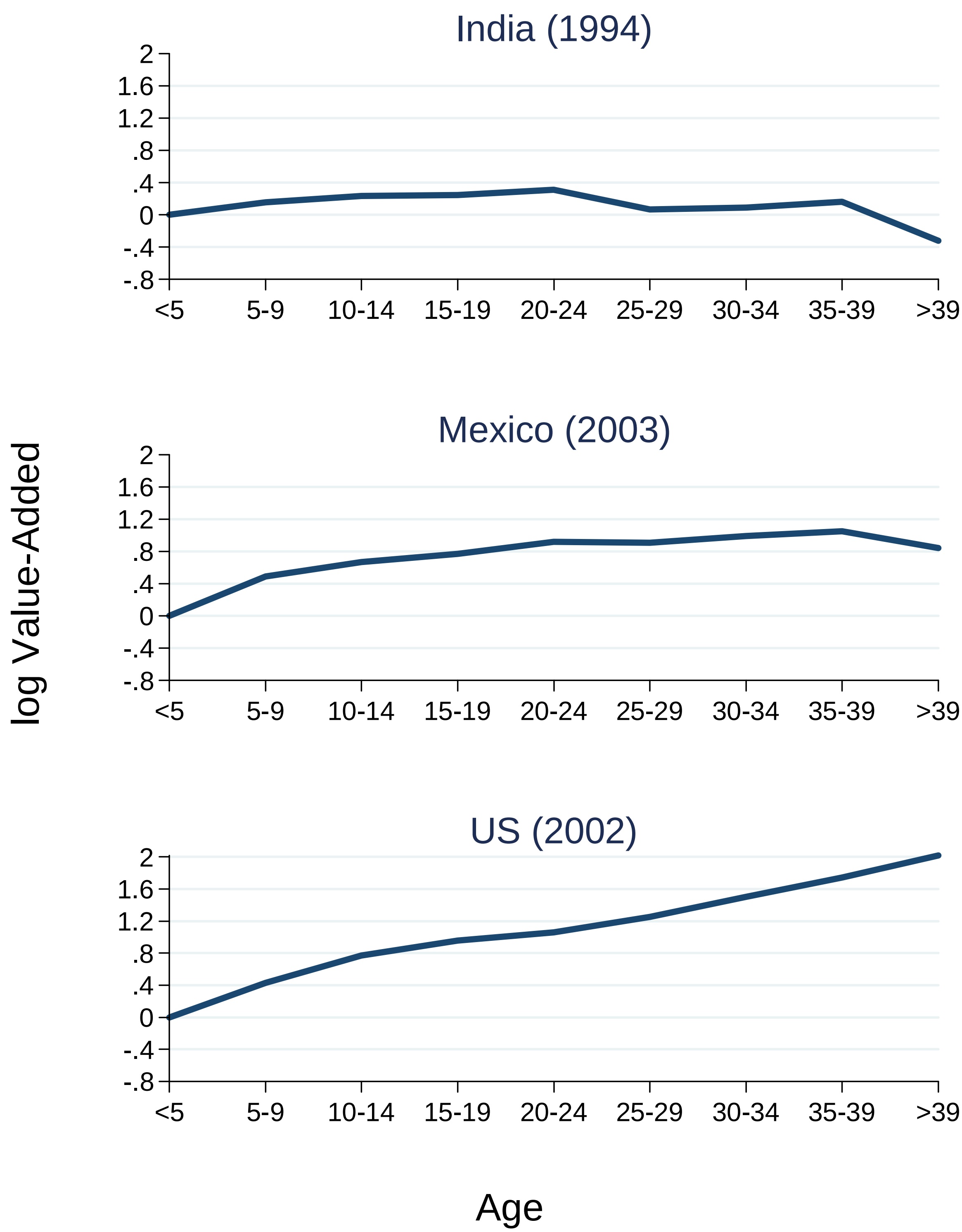

Figure 6: Plant Employment by Age for Formal Indian Establishments

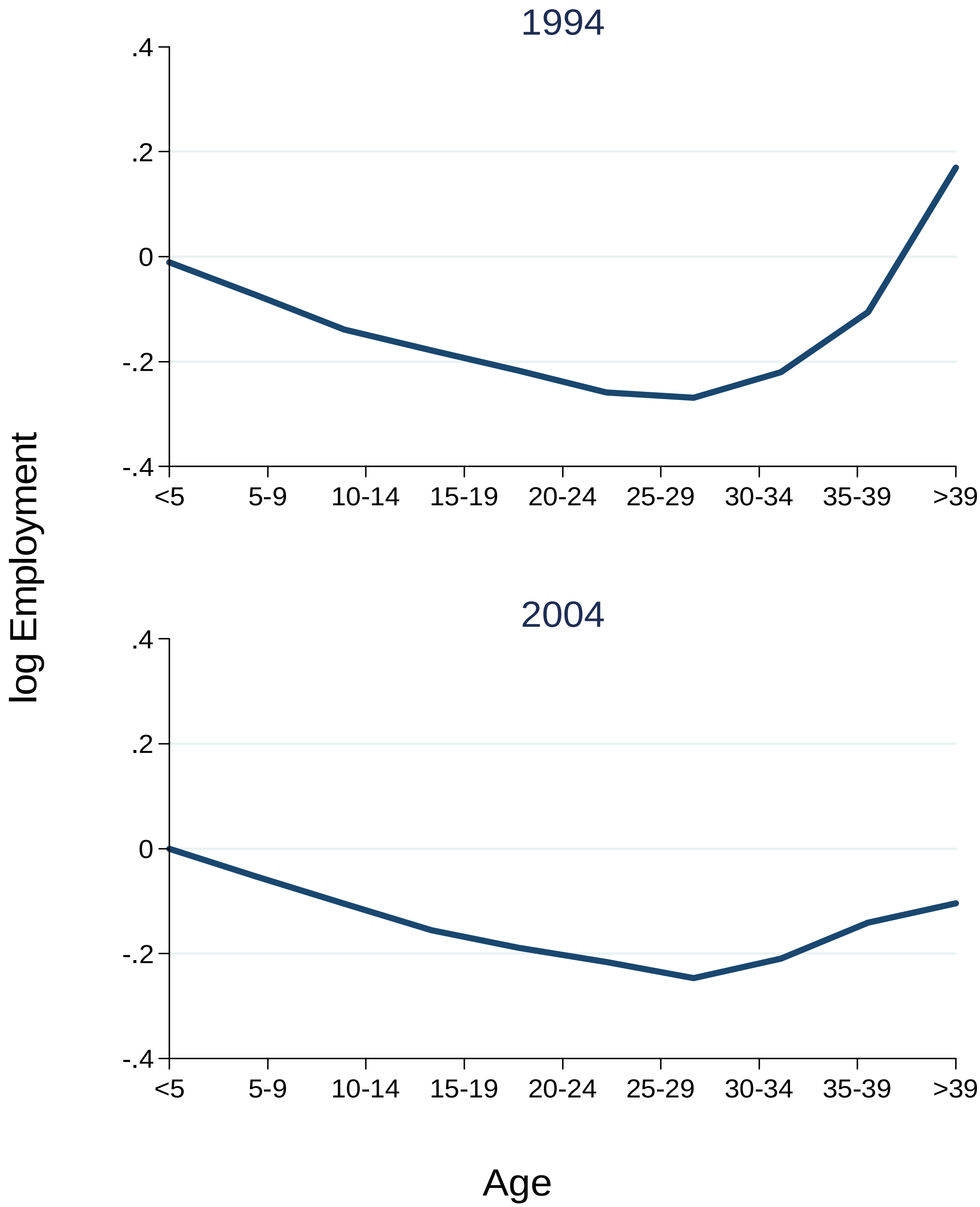

Figure 7: Employment Shares by Age

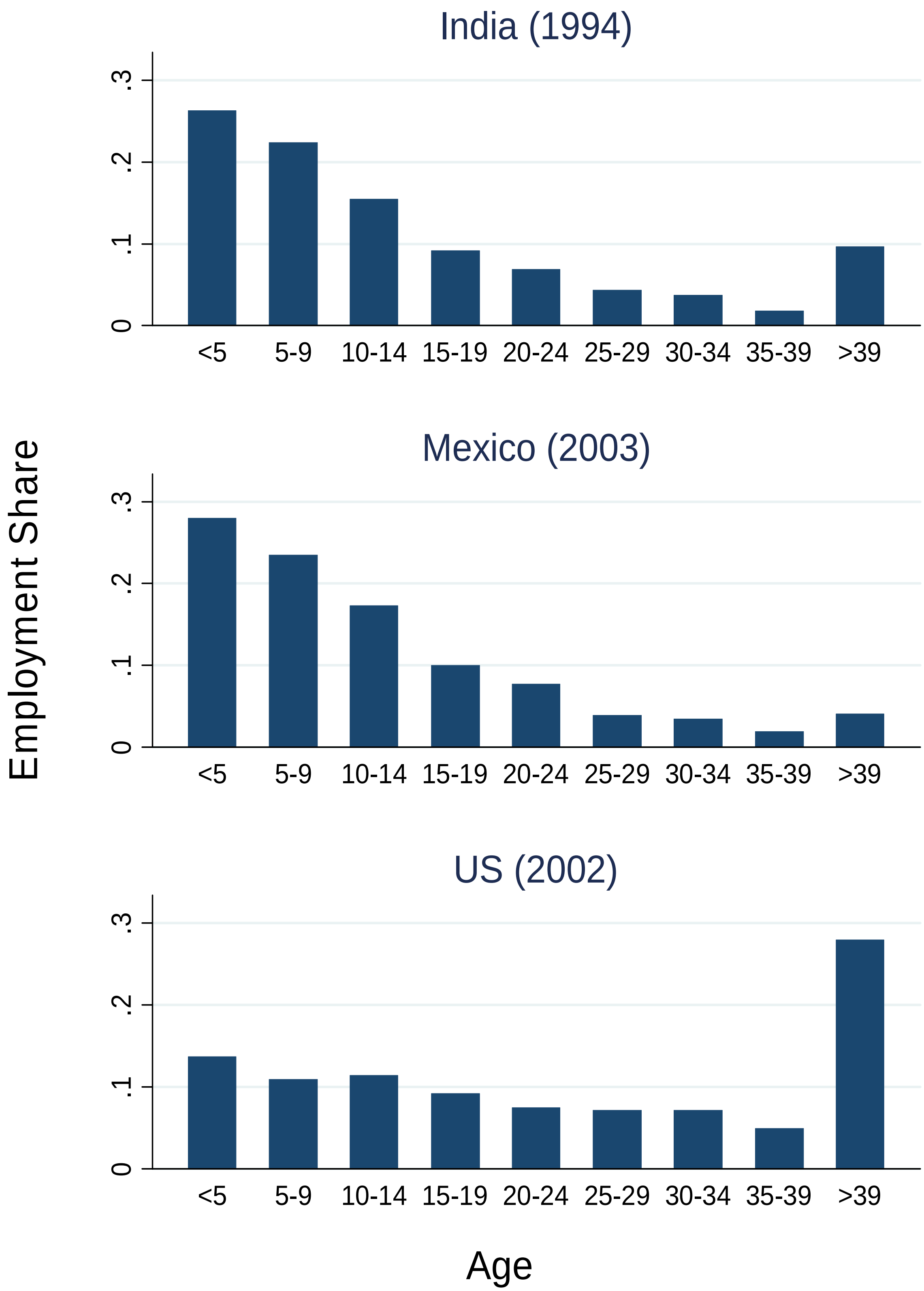

Figure 8: Exit Rate by Age

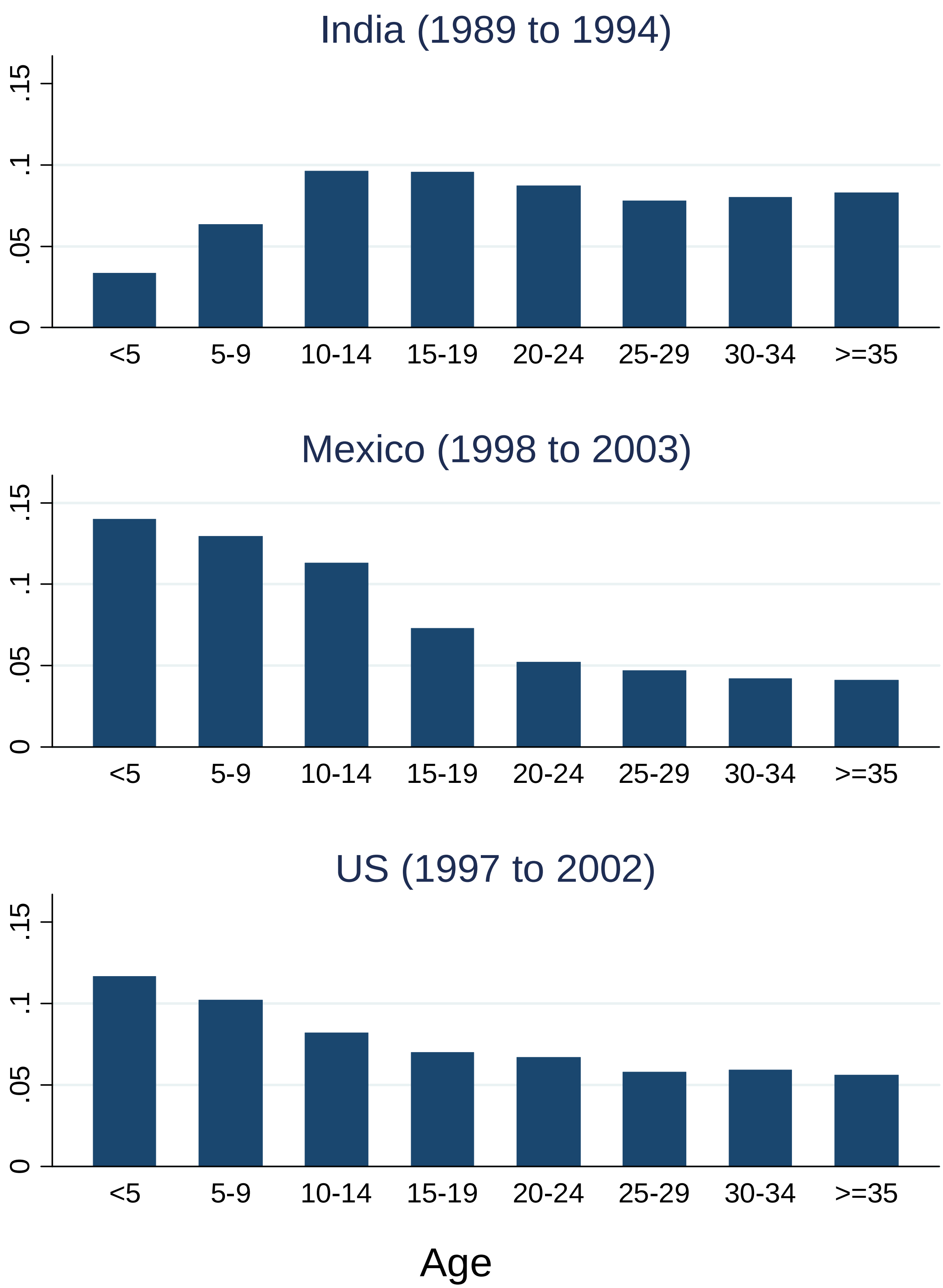

Figure 9: Plant Employment over the Life-Cycle

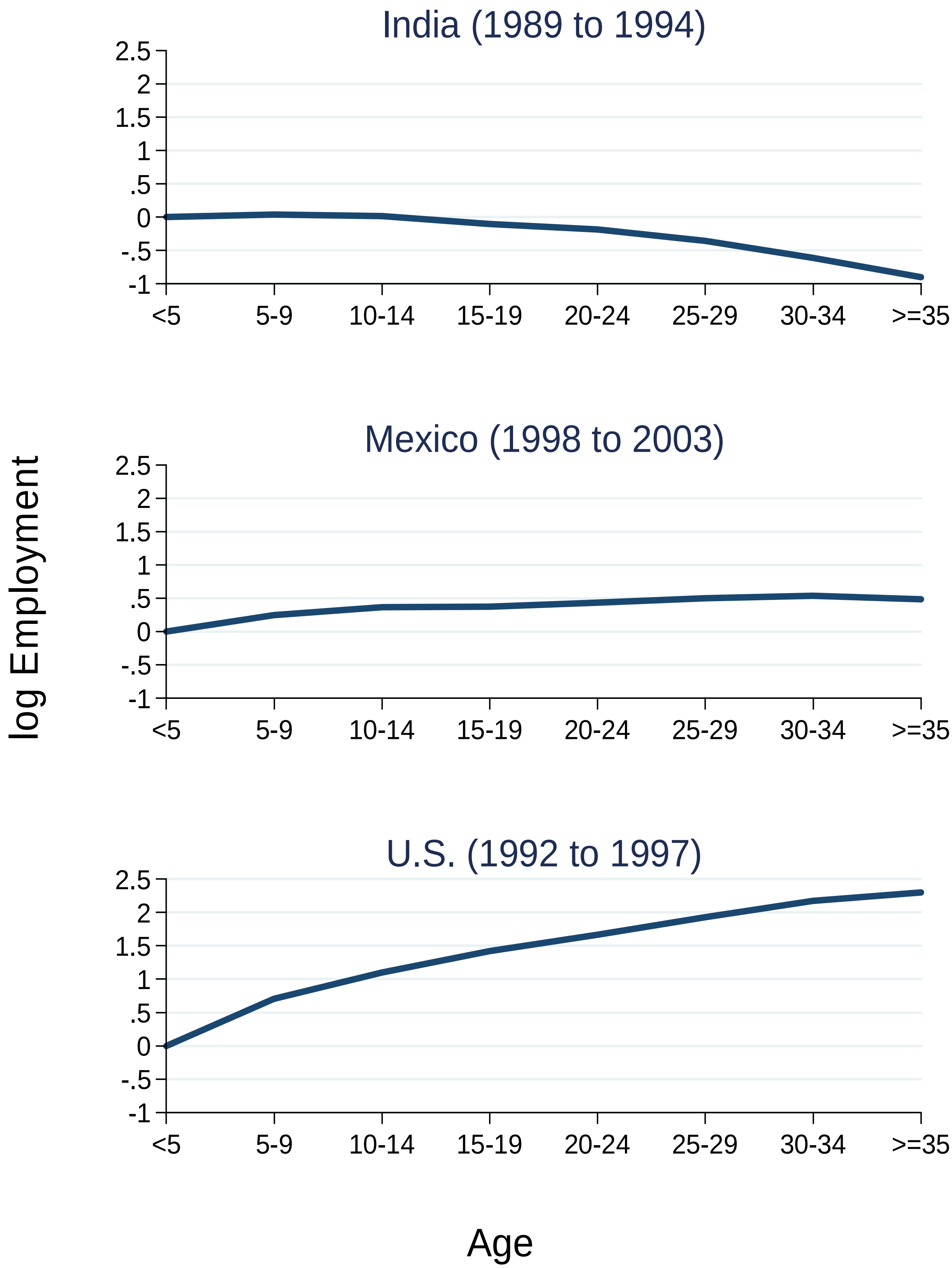

Figure 10: Manufacturing Productivity in Mexico and India

Figure 11: Employment Growth in the U.S. (1992-1997)

All Plants vs. Survivors

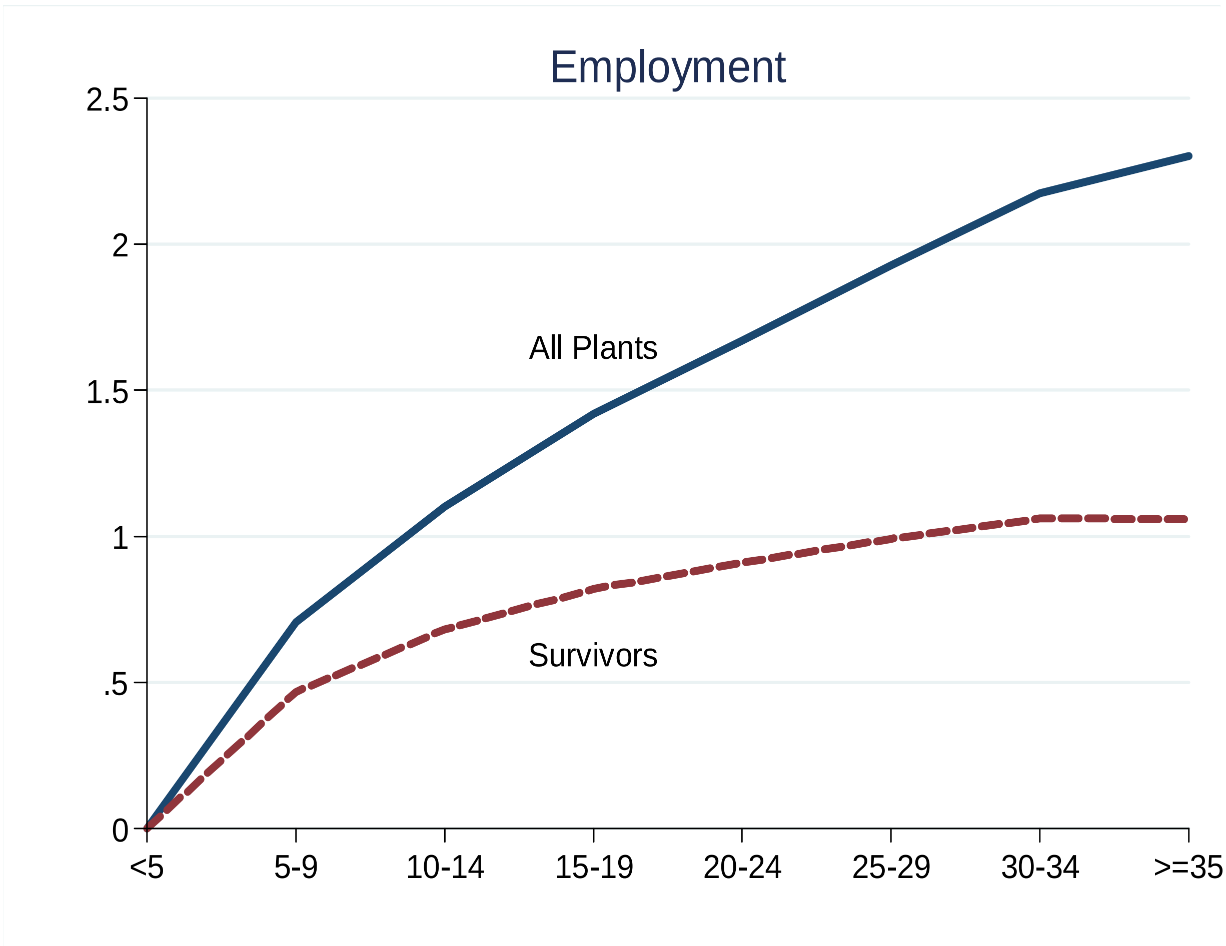

Figure 12: Mean log Employment vs. log Mean Employment

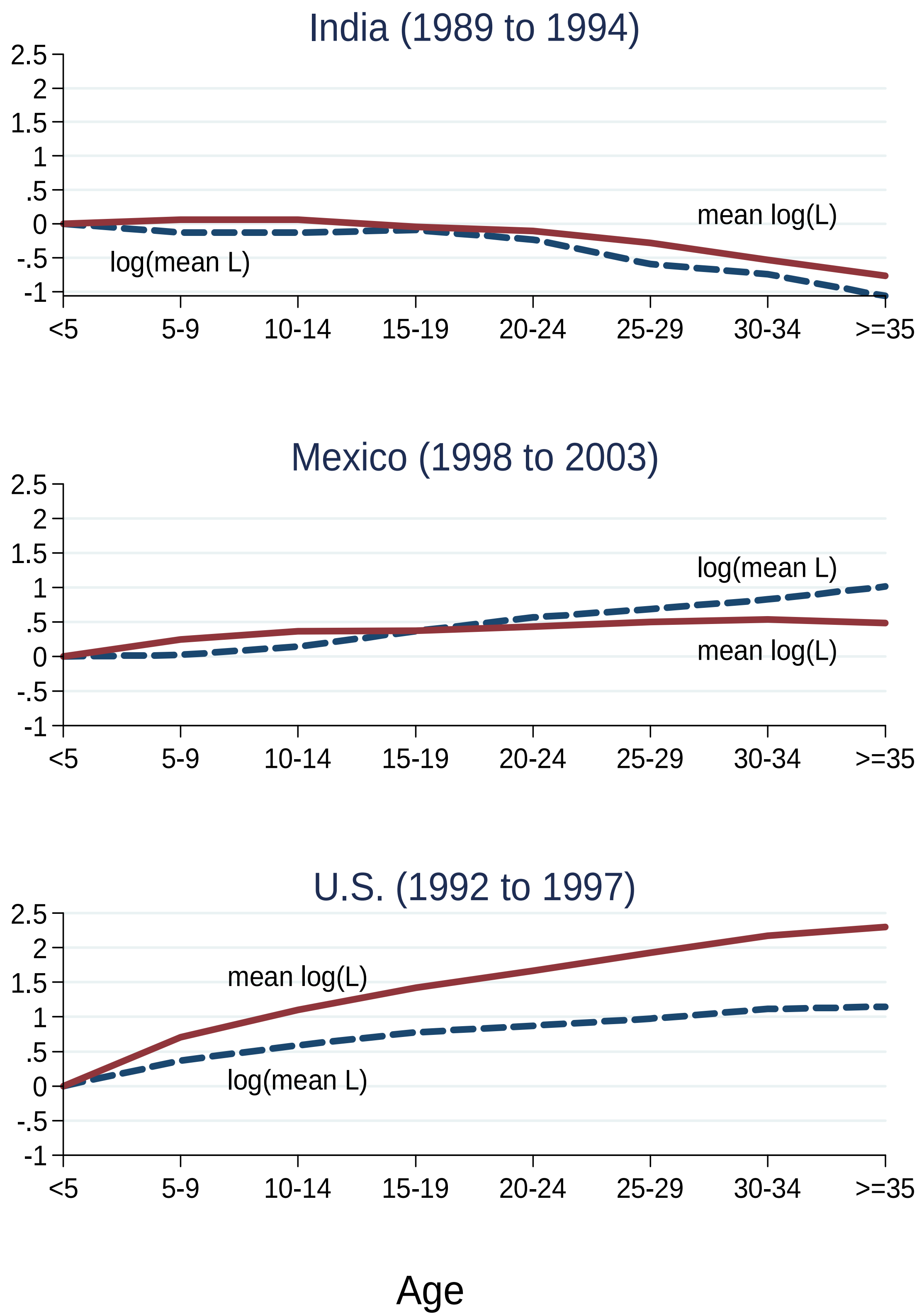

Figure 13: Establishment Productivity Over the Life-Cycle

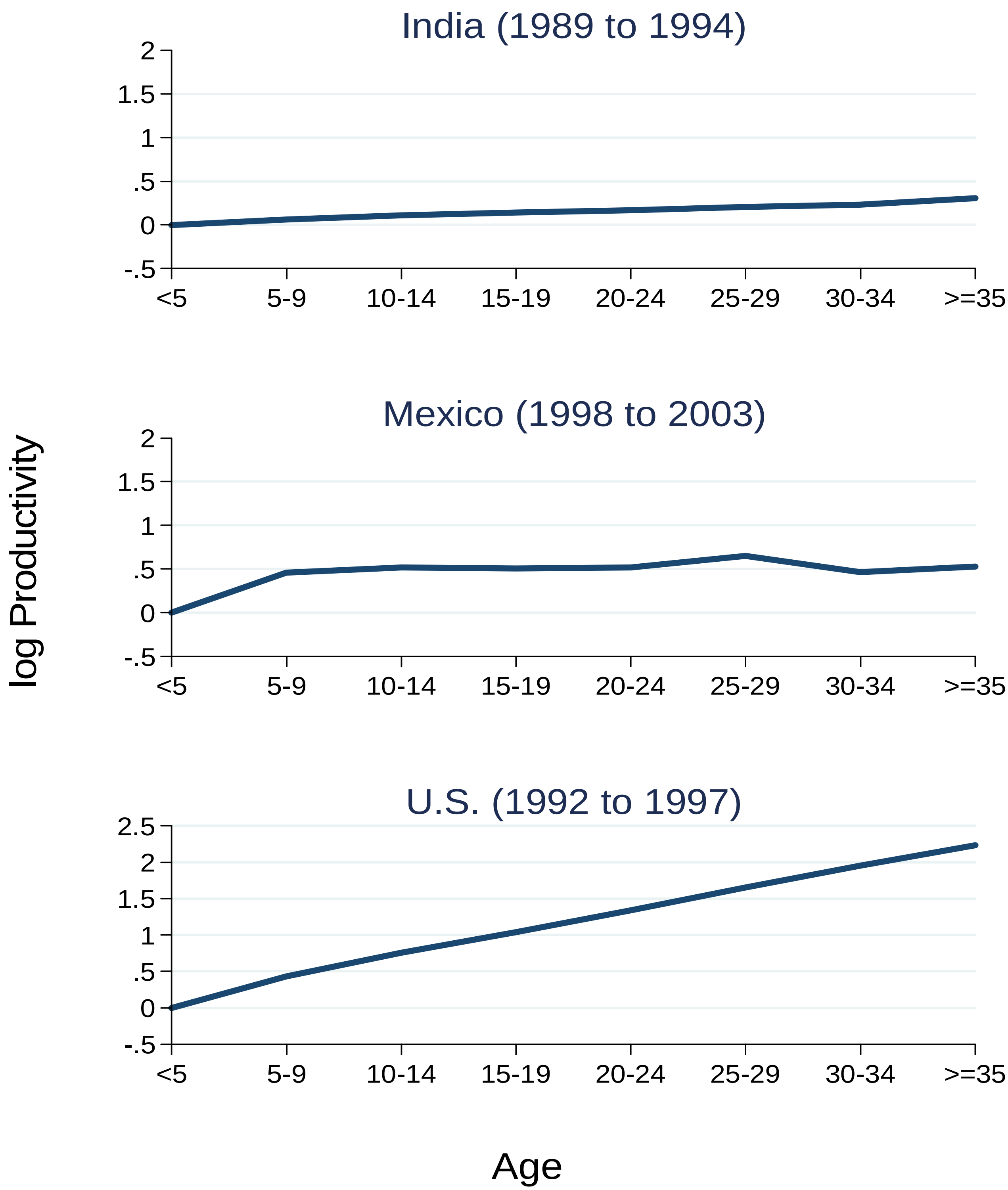

Figure 14:
Employment Share by Age with U.S. Sectoral Shares

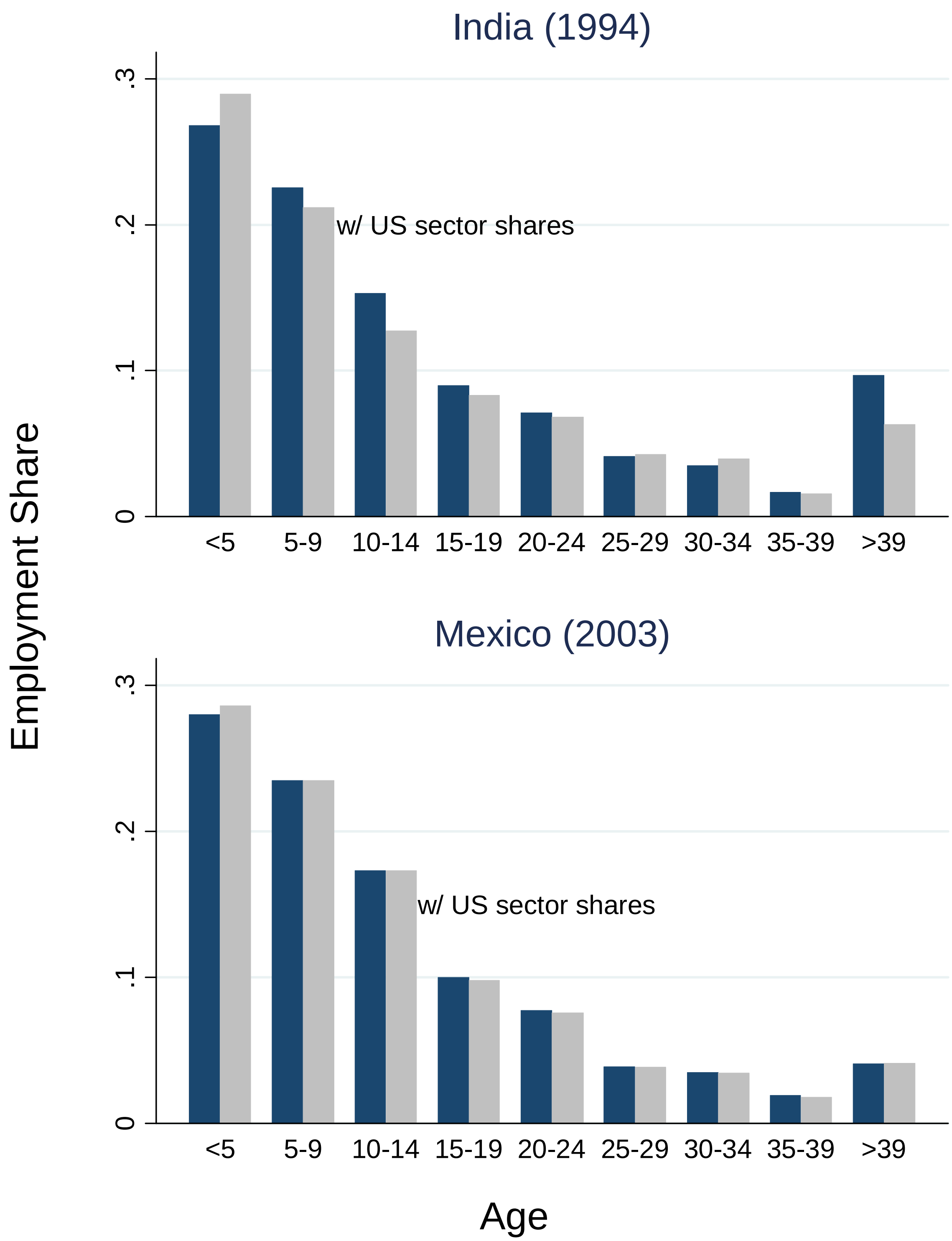

Figure 15:
Density of Establishment by Size with U.S. Sectoral Shares

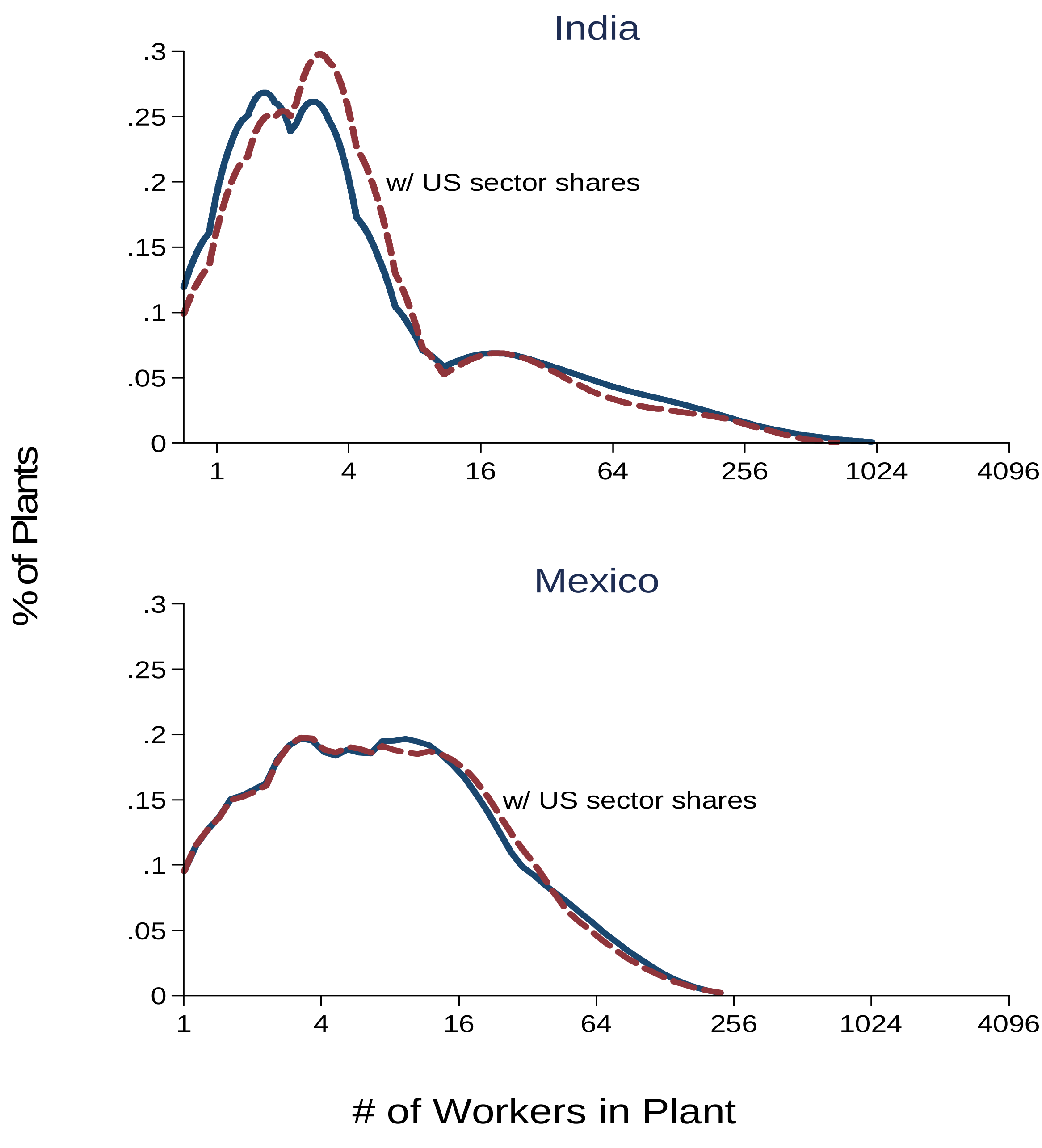

Figure 16:
Density of Establishment by Size in India, 1989 and 2004

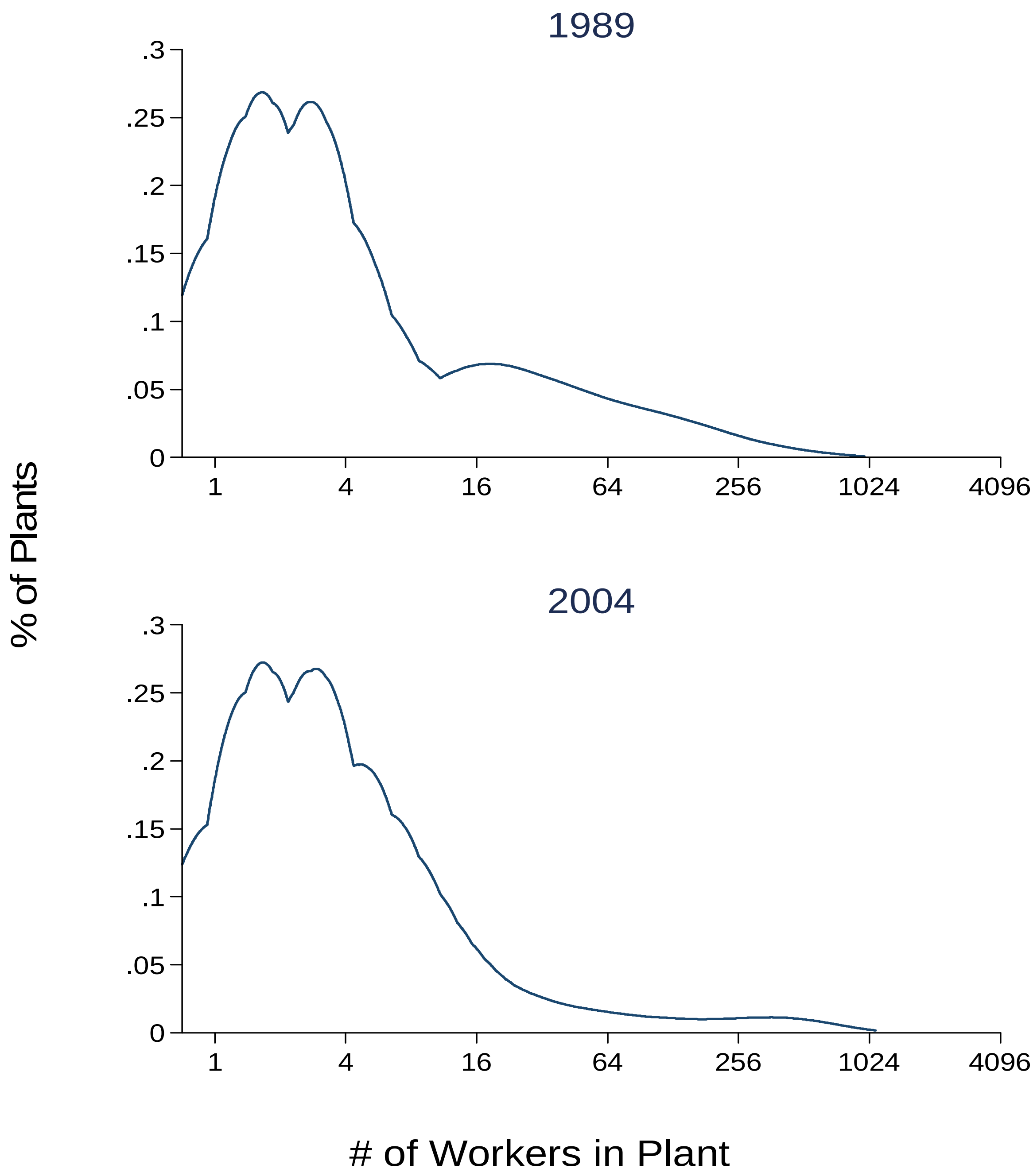

Table 1: Indian Sample

Establishments (thousands)

	Observations in Data		With Sampling Weights	
	ASI	NSS	ASI	NSS
1989	46	97	90	13,760
1994	53	159	107	12,304
1999	24	55	117	14,032
2004	39	83	122	17,054

Table 2: Indian Sample

Workers (thousands)

	All Workers		Paid Workers		Workers in
	ASI	NSS	ASI	NSS	Family Firms
1989	7,096	25,764	6,984	2,382	21,523
1994	7,901	20,580	7,780	2,225	13,331
1999	7,906	29,109	7,906	6,347	19,815
2004	8,180	36,408	8,114	8,849	23,679

Note: We define Family Firms as establishments with *only* unpaid workers.

Table 3: Share of Unpaid Workers by Section in India

	1989	2004
Food and Beverages	.72	.62
Tobacco	.85	.89
Textiles	.66	.62
Apparel	.82	.75
Lumber and Wood Products	.95	.91
Furniture and fixtures	.90	.62
Paper and paper products	.45	.53
Printing and publishing	.34	.36
Chemicals	.35	.39
Petroleum and Coal	.12	.13
Rubber and Plastics	.27	.22
Leather and leather products	.77	.42
Stone, clay, glass, and concrete	.77	.51
Primary metals	.06	.08
Fabricated metals	.61	.49
Industrial machinery	.18	.26
Electrical equipment and machinery	.09	.25
Transportation equipment	.08	.09
Instruments	.21	.14

Table 4: Mexican Census

(in thousands)

	Plants	Workers	Paid Workers	*Formal* Paid Workers
1998	344	4,226	3,793	877
2003	329	4,199	3,387	661
2008	437	4,661	3,277	505

Note: We define Formal Paid Workers as workers paying social security taxes (IMSS). Unpaid workers are legally exempt. See paper for details.

Table 5: Distribution of Establishments by Size

	25th	Median	75th
India	2	3	9
Mexico	3	7	17
U.S.	18	48	152

Notes: 1994 ASI and NSS in India, 2003 Census in Mexico, and the 2002 Census of Manufactures in the U.S. The size of establishments is measured by employment. 25^{th} and 75^{th} are percentiles of *establishments*.

Table 6: Distribution of Employment by Establishment Size

	25th	Median	75th
India	2	5	57
Mexico	11	24	55
US	272	868	2,773

Notes: 1994 ASI and NSS in India, 2003 Census in Mexico, and the 2002 Census of Manufactures in the U.S. The size of establishments is measured by employment. 25th and 75th are percentiles of *employment*.

Table 7: Elasticity of Establishment Size to Age

	India	U.S.
Food and Beverages	-.000	.066
Textiles	.003	.069
Apparel	.000	.048
Lumber and Wood Products	.000	.047
Furniture and fixtures	-.001	.063
Paper and paper products	.011	.049
Printing and publishing	.001	.049
Chemicals	.005	.050
Petroleum and Coal	.022	.028
Rubber and Plastics	.006	.056
Leather and leather products	-.004	.050
Stone, clay, glass, and concrete	.001	.032
Primary metals	.004	.070
Fabricated metals	-.001	.053
Industrial machinery	-.001	.053
Electrical equipment and machinery	.036	.067
Transportation equipment	.002	.072
Instruments	.029	.057

Notes: Entries are coefficients from regression of log employment on age on the 1994 cross-section for India and the 2000 cross-section for the US. Age is truncated at 25.

Table 8: 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(TFPQ)	2.1% per year for all models (U.S. average TFP growth)
$A_{a,i}$	TFPQ 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, TFPQ	Matches average rate for each 5 year age cohort in the U.S.; slope with respect to ln(TFPQ) in the U.S. (-0.0225)
$\tau_{a,i}$	Tax rate on revenue by age, TFPQ	Matches average ln(TFPR) in 5 year cohorts in the U.S. or India; slope of ln(TFPR) wrt ln(TFPQ) in the U.S. (0.13) or India (0.56)
σ_e	S.D. of entrant ln(TFPQ)	1.01 (when not zero) to match U.S. entrant TFPQ dispersion
h	Level parameter in the R&D cost function	Set with b to match average U.S. TFPQ growth from age 0 to 30
b	Convexity parameter in the R&D cost function	Set to 100 to roughly match average Indian TFPQ 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 9: % changes when going from U.S. to Indian Life Cycle

Common TFPQ and TFPR within cohorts

	TFPQ by Age	+ Free Entry	TFPQ, TFPR by Age	+ Free Entry
Weighted Average TFPQ	-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				
TFPQ variation by:	**Age**	**Age**	**Age**	**Age**
TFPR 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 10: % changes when going from U.S. to Indian Life Cycle

Dispersion in TFPQ and TFPR within cohorts

	Fixed Entry	Free Entry	Endogenous Entrant Quality	Incumbent Innovation
Weighted Average TFPQ	-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%
Model Ingredients				
TFPQ, TFPR 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 TFPQ as in the U.S.

Table 11: Average Employment per Plant, Models vs. Data

	DATA	Model TFPQ by age	Model TFPQ and TFPR by age	Model TFPQ and TFPR by age, within	Model Endogenous Entrant Quality	Model Incumbent Innovation
U.S.	197	197	197	197	197	197
India	18	160	137	116	122	102
Model Ingredients						
TFPQ variation by:		**Age**	**Age**	Age, **Within**	Age, Within	Age, Within
TFPR variation by:		None	**Age**	Age, **Within**	Age, Within	Age, Within
Endogenous Entrant Quality		No	No	No	**Yes**	No
Incumbent Innovation		No	No	No	No	**Yes**

Note: All of the models have free entry, with the fixed entry cost (in terms of labor) chosen to match the average plant size in the U.S.

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