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THE LIFE CYCLE OF PLANTS IN INDIA AND MEXICO*

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In the United States, the average 40-year-old plant employs more than seven times as many workers as the typical plant 5 years or younger. In contrast, surviving plants in India and Mexico exhibit much slower growth, roughly doubling in size over the same age range. 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 general equilibrium models, we find that the difference in life cycle dynamics could lower aggregate manufacturing productivity on the order of 25 percent in India and Mexico relative to the United States. *JEL* Codes: O11, O47, O53.

I. Introduction

A well-established fact in the United States is that new businesses tend to start small and grow substantially as they age.[1]

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

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Atkeson and Kehoe (2005) suggest that this life cycle is driven by the accumulation of plant-specific organization capital. In 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 (2013) show that even in commodity-like markets, establishment growth is largely driven by rising demand for the plant's products as it ages.

This article examines the importance of establishment-specific intangible capital accumulation over the life cycle for understanding differences in aggregate manufacturing total factor productivity (TFP) between the United States, India, and Mexico. We choose these three countries because they have some of the most comprehensive micro-data on manufacturing establishments. Importantly, the data we use capture the large informal sector as well as formal establishments in these countries. Many available data sets, such as the data on Chinese manufacturing we used in Hsieh and Klenow (2009), are inadequate for measuring the life cycle because they only survey large establishments.

As preliminary evidence, consider the relationship between establishment employment and age in India and Mexico shown in Figure I. In the United States, 40-year-old manufacturing plants are more than seven times larger than plants under the age of 5 in terms of employment. In India, by contrast, 40-year-old manufacturing plants are only 40 percent 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. What differs between the United States 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 twice as large as their 25-year-old counterparts. These facts are consistent with establishments accumulating less organization capital in India and Mexico than in the United States.[2]

Why would plants in India and Mexico invest less in organization capital? The returns to such investments might be lower in India and Mexico for a multitude of reasons. Large plants could

2. We briefly present more limited evidence for the United Kingdom, Canada, France, Italy, and Spain. The United States exhibits faster life cycle growth than any of these countries, and India slower growth than any of these countries. Life cycle growth in the United Kingdom and Canada is, surprisingly, similar to Mexico.

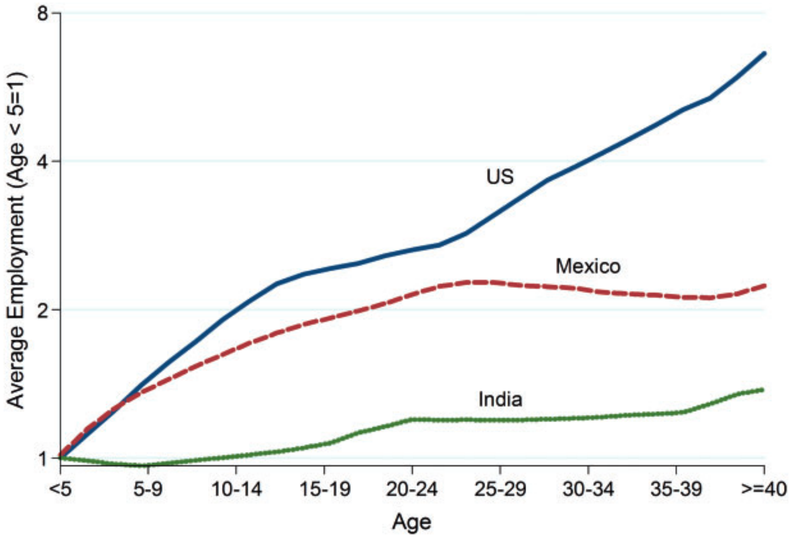

FIGURE I

Plant Employment by Age in the Cross-Section

Data from 2010–2011 ASI-NSS (India), 2003 Economic Census (Mexico), and the 2002 Manufacturing Census (United States). Employment in the youngest group (age < 5 years) is normalized to 1 in each country. The figure gives employment per operating plant versus plant age in the cross-section. In Mexico, employment includes paid and unpaid workers at fixed-location establishments. For the United States, employment covers all manufacturing establishments with at least one employee.

face higher taxes or higher labor costs. Levy (2008) argues that payroll taxes in Mexico are more stringently enforced on large plants. Bloom et al. (2013) suggest that contract enforcement problems make 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 relaxed financial constraints as the firm grows.[3] 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.

3. Cooley and Quadrini (2001), Cabral and Matta (2003), Albuquerque and Hopenhayn (2004), and Clementi and Hopenhayn (2006) are examples.

Consistent with these stories, we find that the gap in the average revenue product of inputs between high- and low-productivity establishments is five to six times larger in India and Mexico than in the United States—as if more productive 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 general equilibrium (GE) models based on Melitz (2003) and Atkeson and Burstein (2010). We focus on three mechanisms. First, if postentry 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 inframarginal 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 percent drop in aggregate TFP. When we try to explain the life cycle patterns as endogenously arising from tax-like wedges, we account for about one-third of the U.S.-Indian difference but over-explain by one-half the U.S.-Mexican difference.

The article proceeds as follows. Section II describes the data. Section III presents the basic facts about the life cycle of plant employment in India, Mexico, and the United States. Section IV provides evidence on whether slower productivity, steeper barriers, or both account for the life cycle of employment 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 are representative across the age distribution. A typical establishment-level data set has information only on plants above a certain size threshold. This is problematic for measuring the life cycle if most new establishments are small. Our analysis focuses on the United States, Mexico, and India because these countries have data covering almost the entire distribution of employment by establishment age.

For the United States, 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.[4] 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 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.[5] We have data every five years starting in 1963, so we group establishments into five-year age groupings. For our analysis, we use the censuses from 1992, 1997, and 2002 because 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 because our focus there was on the dispersion of the ratio of plant output to inputs. Here, our main focus is on plant employment, which is not likely to be significantly biased in the administrative record establishments.

The data sets we use for Indian manufacturing are the Annual Survey of Industries (ASI) and the Surveys of Unorganized Manufacturing conducted by the National Sample Survey Organization (which we abbreviate as NSS). The ASI is a census of manufacturing establishments with more than 100 employees and a random sample of formally registered establishments with fewer than 100 employees.[6] The NSS is a sample of

4. Such nonemployee establishments accounted for only 0.29% of total manufacturing sales in 2007.

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

6. 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 fewer than 100 workers were surveyed in the ASI prior to 1994–1995. The sampling

the self-employed with fewer than 10 employees. The ASI and the NSS collect data over the fiscal year (April 1 through March 30). We have the ASI every year from 1980–1981 to 2009–2010. The NSS data on unorganized manufacturing is available for five years: 1989–1990, 1994–1995, 1999–2000, 2005–2006, and 2010–2011.

Establishment age is critical to our analysis. The plant's year of initial production is self-reported in the Indian data. This variable is available for all years in the ASI and in three years in the NSS (1989–1990, 1994–1995, and 2010–2011). In the ASI, the year of initial production is defined as the year production began at the specific physical location. In addition the ASI's instruction manual states that the "year of initial production is to be decided irrespective of ownership changes or new registration." In the NSS, the year of initial production is defined in the same manner for establishments with a fixed physical location. For establishments in the NSS that do not have a fixed physical location, the birth year is defined as the year when the establishment's owner began production (not necessarily in the same physical location). We focus on the three years (1989–1990, 1994–1995, and 2010–2011) for which the NSS provides age information. We combine the NSS data for 1989–1990 and 1994–1995 with the ASI data for the same years and the 2010–2011 NSS with the 2009–2010 ASI. We refer to the combined data set as the ASI-NSS.

To make the Indian data comparable to the U.S. data, we restrict the analysis to sectors that are also classified as manufacturing in the U.S. data.[7] The variables we use from the ASI and the NSS are establishment age, the number of paid employees, contract workers, unpaid workers, wage and nonwage compensation, total capital stock, value added, and four-digit industry code. Wage and compensation data are only available for establishments with paid employees or contract workers. The NSS separately provides the number of full-time and half-time workers. The ASI and the NSS use the same industry

probability of the smaller plants in the ASI decreased to roughly one-seventh after 1994–1995.

7. This primarily removes auto and bicycle repair shops, which are classified as manufacturing in the Indian data. Repair shops account for roughly 20 percent of all establishments in the Indian data.

classification (about 400 industries each year). Establishment identifiers are provided in the ASI starting in 1998–1999; the NSS does not have establishment identifiers.

For Mexico, we use data from the Mexican Economic Census, 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. We have access to the micro-data of the Mexican censuses in 1998, 2003, and 2008. To make the Mexican data comparable to the U.S. data, we restrict our attention to establishments in the manufacturing sector.[8] The variables we use from these data are the number of paid employees, contract workers, unpaid workers, hours worked (for each type of worker), the wage bill, labor taxes (paid to Mexico's Social Security Agency) and other nonwage compensation, total capital stock, value added, year of initial production (from which we impute establishment age), and industry (roughly 350 industries in manufacturing). The year of initial production in the Mexican data is self-reported by the establishment. The Mexican census defines this variable as "the year in which the establishment began operation, regardless of whether or not there has been an ownership change since the year in which production began" (our translation). There are no establishment identifiers in the Mexican data, and although the data are a census, there is not enough information in the data to link establishments between census years.

Table I presents the number of establishments and total employment in our data. 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 I, 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.

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

TABLE I

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	39	96	77	13,678	6,211	25,606
1994–95	45	157	93	12,153	6,953	20,357
2010–11	30	98	103	16,957	9,394	33,306

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

Notes. Entries are in thousands. Data from the ASI-NSS (India), Economic Census (Mexico), and Manufacturing Census (United States). For India and Mexico, the number of workers include unpaid workers and contract workers.

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 United States. We control for four-digit industries—all the facts we show are within-industry patterns, averaged across all the industries using the value-added share of each industry as weights.

We begin by presenting evidence from the *cross-sectional* relationship between employment per surviving plant and plant age (Figure I). The data are from the 2010–2011 ASI-NSS for India, 2003 Economic Census for Mexico, and 2002 Manufacturing Census in the United States. In the U.S. cross-section, the average operating plant over the age of 40 is more than seven times larger than the average plant under the age of 5. In contrast, 40-year-old Indian plants are no larger than young 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 be higher in India and Mexico so that fewer plants survive to old age. Figure II plots exit rates by age in the three countries, which we computed from two separate years for each country (1992 to 1997 from the U.S. Manufacturing Census, 1994–1995 to 2010–2011 from the Indian ASI-NSS, and 1998 to 2003 from the Mexican Manufacturing Census).[9] Exit rates in India and Mexico are generally no higher than in the United States.

Relatedly, old plants may not matter much for aggregates in any of our countries. Figure III shows the distribution of employment by establishment age in the cross-section for all three countries. The employment share of each age group is a function of employment per surviving plant of each age, the fraction of plants surviving to each age, and the size of each cohort at birth. As Figure III indicates, employment shares decline with age in all

9. For India the 15 years between observations entailed some imputation. Specifically, we assume that the number of plants of cohort a in 2010–11 relative to the number of plants of the same cohort in 1994–1995 is given by $(1-\delta_{a+1})^5(1-\delta_{a+2})^5(1-\delta_{a+3})^5$ where a denotes five-year groupings of age in 1994–1995 and δ_{a+1} denotes the average annual exit rate from age a to age $a+1$ (δ_{a+2} and δ_{a+3} are defined analogously). We assume that exit rates are constant after age 40. We have data from eight age cohorts from which we impute the eight exit rates shown in Figure II.

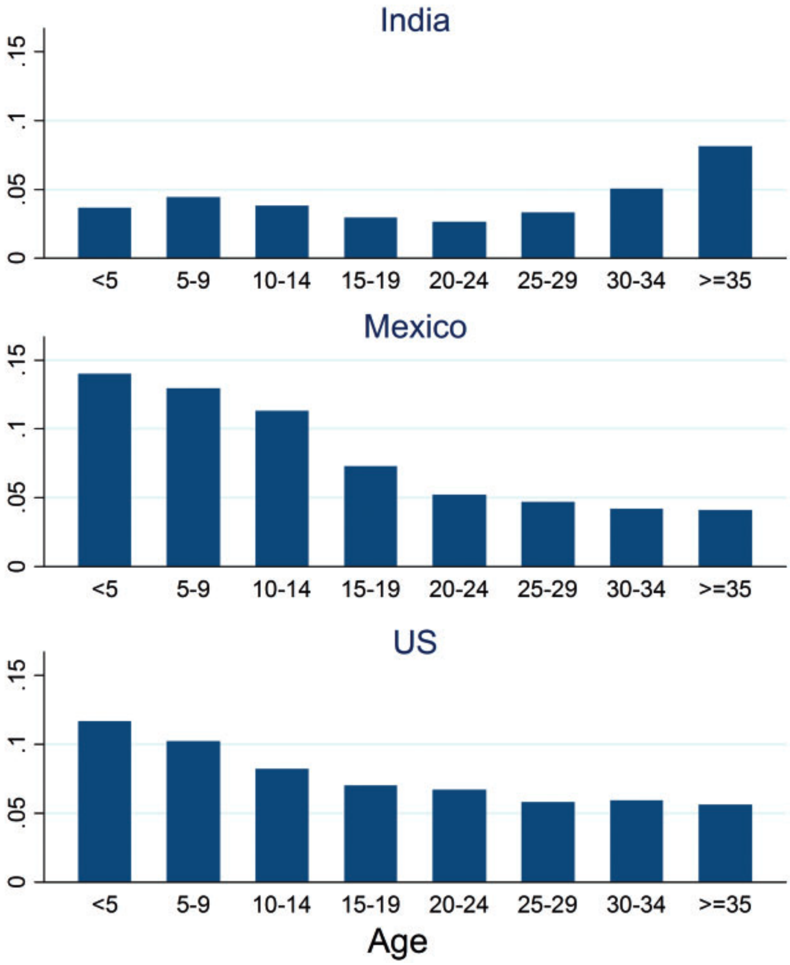

FIGURE II

Exit Rate by Age

Exit rates are calculated from 1992 to 1997 (U.S. Manufacturing Census), from 1994–1995 to 2010–2011 (Indian ASI-NSS), and 1998 to 2003 (Mexican Manufacturing Census). See text for details.

three countries (the spike in the last age group is due to pooling of plants 40 and older). But the decline is steeper in India and Mexico than in the United States. The employment share of plants 40 years or older is less than 5 percent in India and Mexico versus almost 30 percent in the United States. Thus old

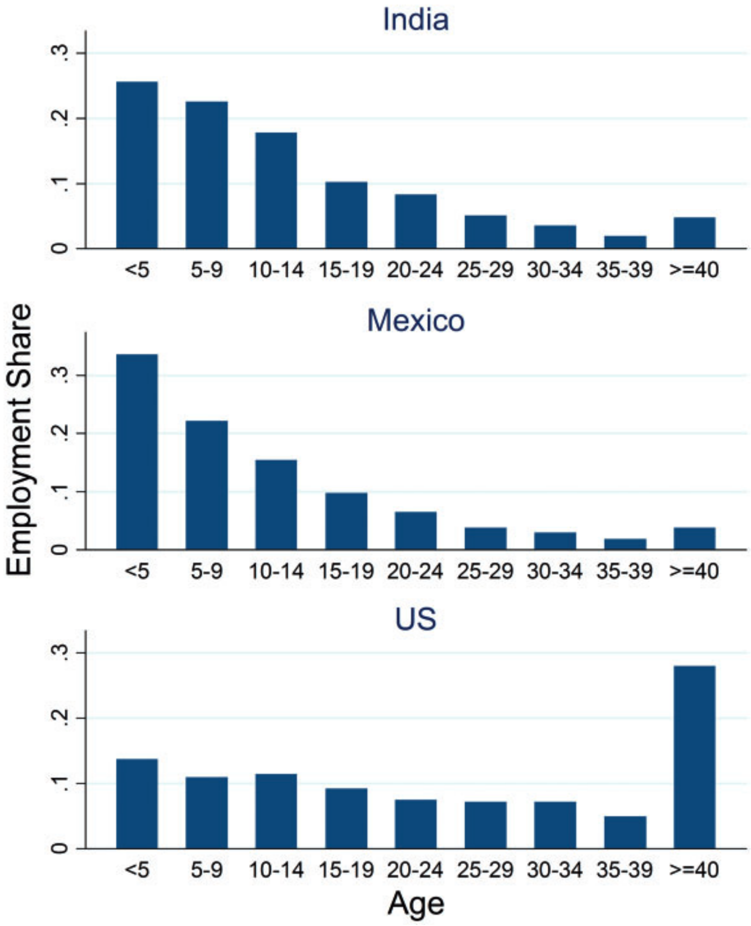

FIGURE III

Employment Share by Age in the Cross-Section

2010–2011 ASI-NSS (India), 2003 Economic Census (Mexico), and 2002 Manufacturing Census (United States). For India, employment includes paid, unpaid, and contract workers. In Mexico employment includes paid and unpaid workers at fixed-location establishments. For the United States, employment covers all manufacturing establishments with at least one employee.

plants seem important enough in the United States relative to India and Mexico to affect aggregate productivity.[10]

10. Figure III also diminishes the concern that our data do not include street vendors in Mexico and nonemployee establishments in the United States. Although

These patterns are remarkably robust. Older plants are bigger relative to younger plants in the United States compared to India or Mexico in all years for which we have data, and when using U.S. industry value-added shares to weight industries in all countries. The pattern also holds up across most sectors. 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 5. In the United States, conversely, 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, size is flat with respect to age in the formal plants of the Indian ASI alone, just as in the pooled NSS-ASI data.[11]

Establishment age might measure different things in the United States, India and Mexico. For example, respondents of the Indian ASI could report their establishment's age from when it became formal.[12] This might understate the age of larger ASI plants relative to smaller NSS plants, biasing our portrait of life cycle growth. Furthermore, better functioning markets might allow new firms in the United States to take over the facilities of firms that went out of business, whereas this type of reallocation might be less common in India and Mexico. If either force were important we would expect higher exit rates in Indian and Mexican plants than for U.S. plants, ceteris paribus. We do not see this pattern in the exit rates shown in Figure II. Another concern is that NSS respondents that do not produce in a fixed location report their age from the time the *owner* began production. However, establishments without a fixed location account for only 5.7 percent of all establishments and 3.8 percent of total

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.

11. An interesting question is whether the life cycle of firm employment differs from the life cycle of an establishment. The Mexican and Indian data do not identify the owner of the plant. However, starting in 2001–2002, the Indian ASI provides information on the number of other establishments owned by the parent company. These data indicate that the parent company of a formal Indian plant under the age of 5 also owns 0.85 additional plants. In turn, the parent company of a 40-year-old plant also operates 1.2 additional plants.

12. In a study of informal enterprises in 13 developing countries (including India), however, La Porta and Shleifer (2008) find that the vast majority of formal businesses were never informal.

employment in Indian manufacturing. Not surprisingly, when we restrict the 2010–2011 Indian data to only fixed establishments, the relationship between establishment size and age is identical to that shown in Figure I.

Although suggestive, the relationship between plant employment and age in the cross-section conflates size differences between cohorts at birth with employment growth of a cohort over its life cycle. Ideally, we want to measure a cohort of plants over time. However, we do not have a panel. For the United States, we have establishment data from 1963 to 2002 so we can follow a synthetic cohort over 40 years. In India, we have data on establishment age for 1989–1990, 1994–1995, and 2010–2011 so we can follow cohorts over 20 years. In Mexico, we have data for 1998, 2003, and 2008 so we can follow cohorts for up to 10 years.

Given these data limitations, we measure the life cycle by following synthetic cohorts over time. For Mexico, we compare the average employment of operating establishments of each cohort in 1998 with the average employment of the surviving plants from the same cohort in 2003. We do this for all the cohorts grouped into five-year age bins. If we assume that every cohort experiences the same employment growth and exit rate over its life cycle, we can impute the life cycle from the change in average plant employment from 1998 to 2003 for each cohort. We do the same for the United States by comparing average employment of each cohort in 1992 to the average employment of its surviving members in 1997.[13] In India, we measured growth of each cohort (defined as five-year groupings of age) from 1994–1995 to 2010–2011 (the most recent years with plant age information in the ASI-NSS).[14]

Figure IV presents the cumulative growth in average plant employment with age calculated in this manner. In India, the

13. We did not use 2002 versus 1997 U.S. data here because the U.S. industry classification changed from 1997 to 2002. Recall that we calculate statistics within four-digit industries, then take weighted averages across industries.

14. Because the Indian samples are further apart than our five-year age bins, some imputation is necessary. We assume the growth rate from 1994–1995 to 2010–2011 of a given cohort is a polynomial in age $g_a = \sum_{j=1}^{3} [\gamma_1(a+j) + \gamma_2(a+j)^2 + \gamma_3(a+j)^3 + \gamma_4(a+j)^4]$ where a represents the age of the cohort (in five-year bins) in 1994–1995. We estimate $\gamma_1, \gamma_2, \gamma_3$, and γ_4(the coefficients of the polynomial in age) from the growth rate of eight cohorts from 1994–1995 to 2010–2011. We then impute the growth of average employment over the life cycle by cumulating the estimated coefficients of the polynomial in age.

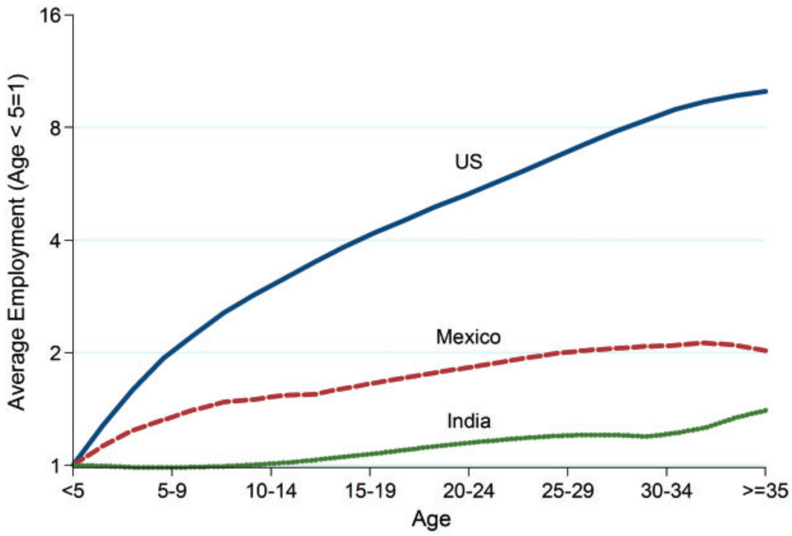

FIGURE IV

Average Employment over the Life Cycle

Employment growth imputed from the 1992 and 1997 U.S. Manufacturing Censuses, the 1998 and 2003 Mexican Economic Censuses, and the 1994–1995 and 2010–2011 Indian ASI-NSS. Employment of the youngest age group is normalized to 1 in each country. We compare average employment per surviving plant in a later year to average employment per operating plant in the same cohort in the earlier year. See text for details.

evidence over time suggests that by age 35, average plant employment is 40 percent higher compared to average employment at birth. The evidence from India's cross-sectional data indicated a slightly smaller increase in plant size. For the United States, the evidence over time suggests that average plant size increases by a factor of 10 from birth to age 35; the cross-sectional evidence suggested less than an eightfold increase. In Mexico, the evidence over time is similar to what the cross-section implied for the increase in plant size with age.

On top of exit, a cohort's employment share can decline with age because entering cohorts are growing in size and number. Figure V plots our estimate of the number of establishments on birth for each five-year cohort (we normalize the youngest cohort in our data to 1 in each country). This calculation measures size of each five-year cohort in the last year for which we have data for each country (2002 in the United States, 2008 in Mexico, and

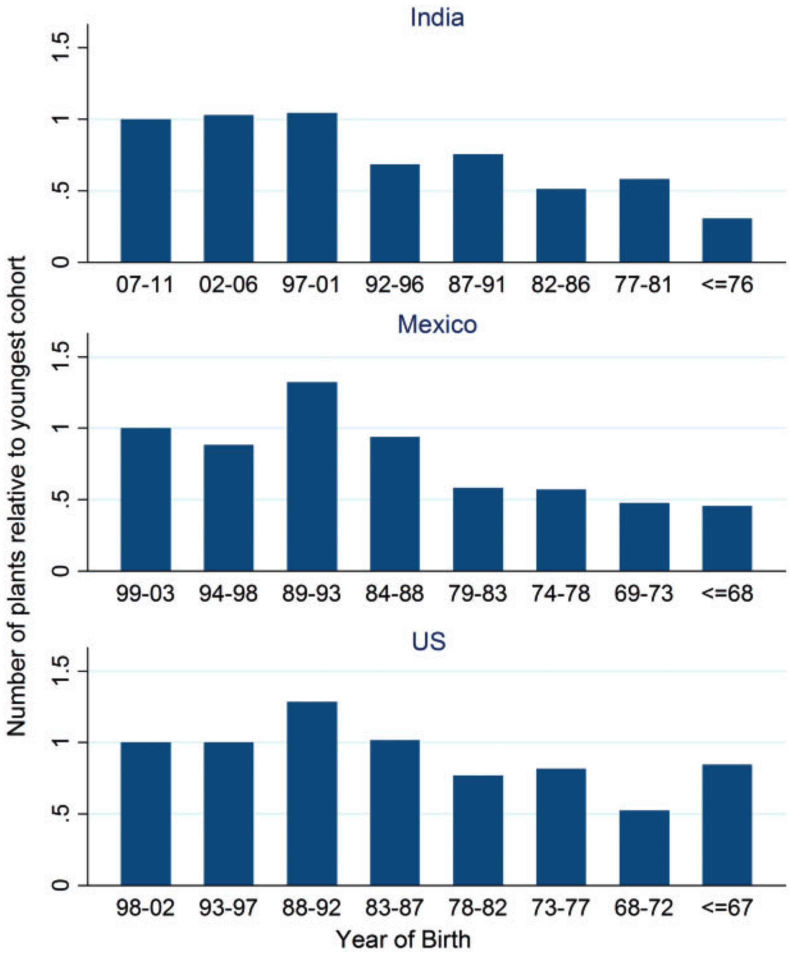

FIGURE V

Number of Plants by Birth Cohort

Cohort size imputed from cohort sizes in 2002 U.S. Manufacturing Census, 2008 Mexican Economic Census, and 2010–2011 Indian ASI-NSS assuming that exit rates by age (shown in Figure II) are the same for all cohorts.

2010–2011 in India). We then impute the size of each cohort at birth by assuming that exit rates by age (shown in Figure II) are the same for all cohorts. Young cohorts are generally larger in India and Mexico, perhaps because Mexico and India began to industrialize after the United States. Thus some of the decline in the employment share with age in the cross-section in Figure III is due to the more rapid growth of entrants in Mexico and India relative to the United States. If there is a steady state in the future with a constant entry rate, we would not expect as large a difference in the employment share of old cohorts between the United States and India and Mexico in the cross-section.

Figure VI shows what employment share with age would look like in a steady state with a constant entry rate. Specifically, Figure VI assumes that all cohorts are of the same size on birth and thus abstracts from differences in cohort size. Furthermore, Figure VI assumes that the growth rate of employment of surviving establishments is given by Figure V (which control for differences in cohort quality) and that exit rates are the same for all cohorts (and given by Figure II).[15] A cohort's employment share declines with age in all three countries; this can stem from exit and/or growing size of entering cohorts. Again, exit rates are no higher in India and Mexico than in the United States. In addition, the growth rate in the size of new cohorts in the United States between 1992 and 1997 was no lower than the growth rate in the size of new cohorts between 1998 and 2003 in Mexico and between 1994–1995 and 2010–2011 in India.[16] These two facts suggests that the steeper decline in the employment share with age in India and Mexico shown in Figure VI cannot be due to higher exit rates or higher growth rates of the size of new cohorts in these two countries.

To drive home that time and cohort effects can matter, Figure VII presents the life cycle for India imputed from employment growth in an earlier period: from 1989–1990 to 1994–1995. This was a period when India undertook major economic reforms, and all the cohorts we follow over these five years were born before these reforms. For comparison, the figure reproduces the life cycle estimated from employment growth from 1994–1995 to 2010–2011. As can be seen, the life cycle before 1994 is remarkably different from the behavior after 1994. Although the post-1994 behavior suggests modest growth over the life cycle, the pre-1994 evidence suggests that by age 35, average plant size

15. Figure VI also assumes that all plants die by age 100.

16. From Table I and Figure V, the average size of new cohorts grew by 27% in the United States between 1992 and 1997. In India, the average size of new cohorts increased by 7% in India between 1994–1995 and 2010–2011 and decreased by 12% in Mexico between 1998 and 2003.

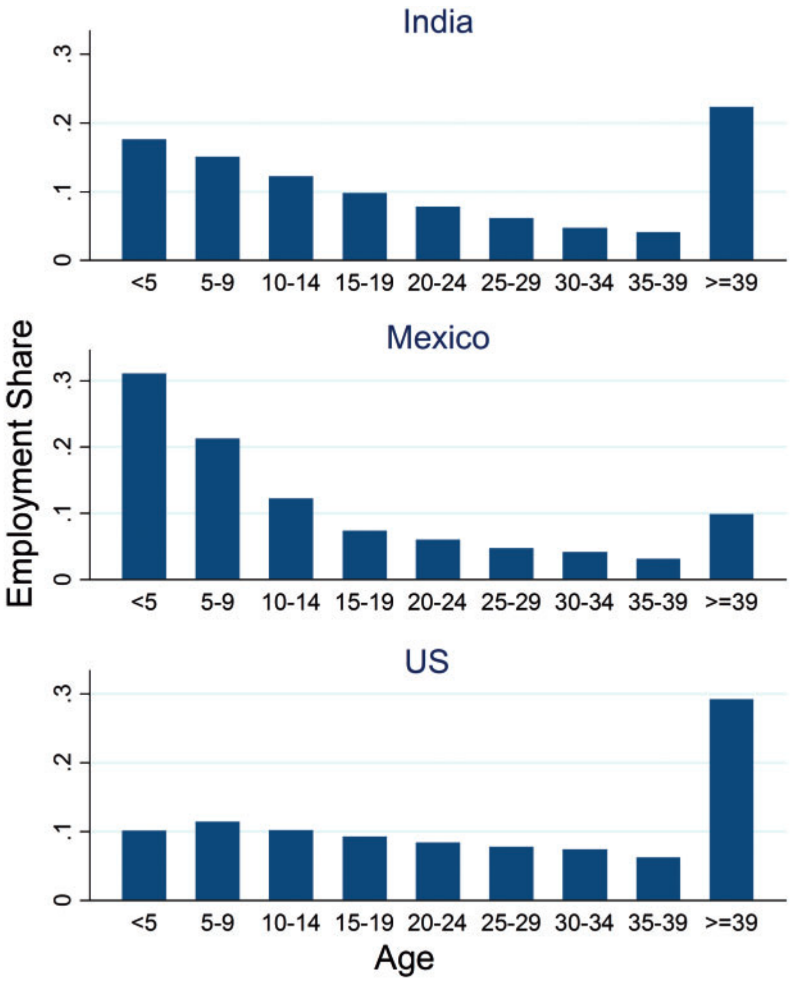

FIGURE VI

Employment Share by Age in Steady State

Steady-state employment share by age assumes constant entry rate and constant average size of entrants. The figure assumes growth in average employment per surviving plant as given by Figure IV and exit rate by age as given by Figure II.

fell to one fourth its size at birth. In sum, although life cycle growth in Indian manufacturing after 1994 is still modest when compared to the United States, it is still significantly faster than observed before the Indian reforms in the early 1990s.

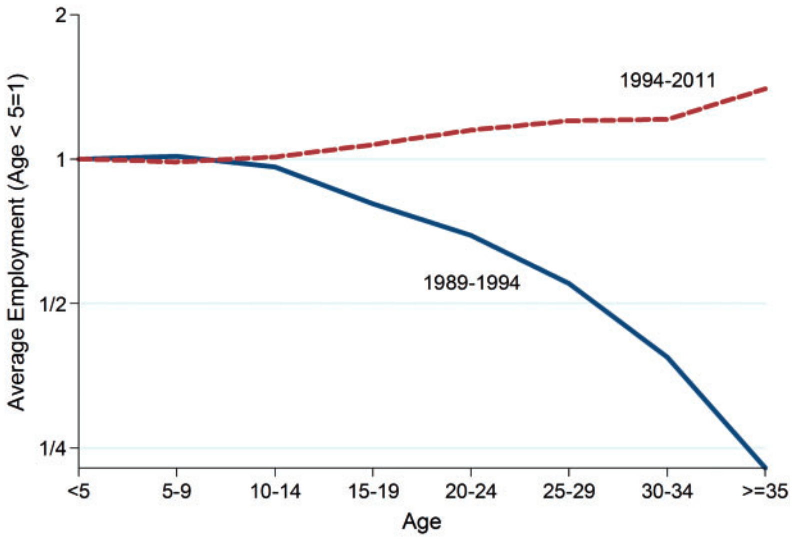

FIGURE VII

Employment Growth in India

Employment growth with age imputed from the ASI and NSS from 1989–1990 to 1994–1995, and from 1994–1995 to 2010–2011.

In contrast, the evidence from Mexico and the United States indicates that the years we focus on are more typical. In the United States, 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 get estimates similar to those shown in Figures IV and VI (based on 1998 to 2003) when we impute the life cycle using the employment change from 2003 to 2008.

Growth in average employment of operating plants in 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), emphasize the role of selection in survivor growth in the United States. We now explore whether the selection effect could explain the difference in the life cycle between the United States and India. Figure VIII presents the growth of surviving establishments in India and the United States.

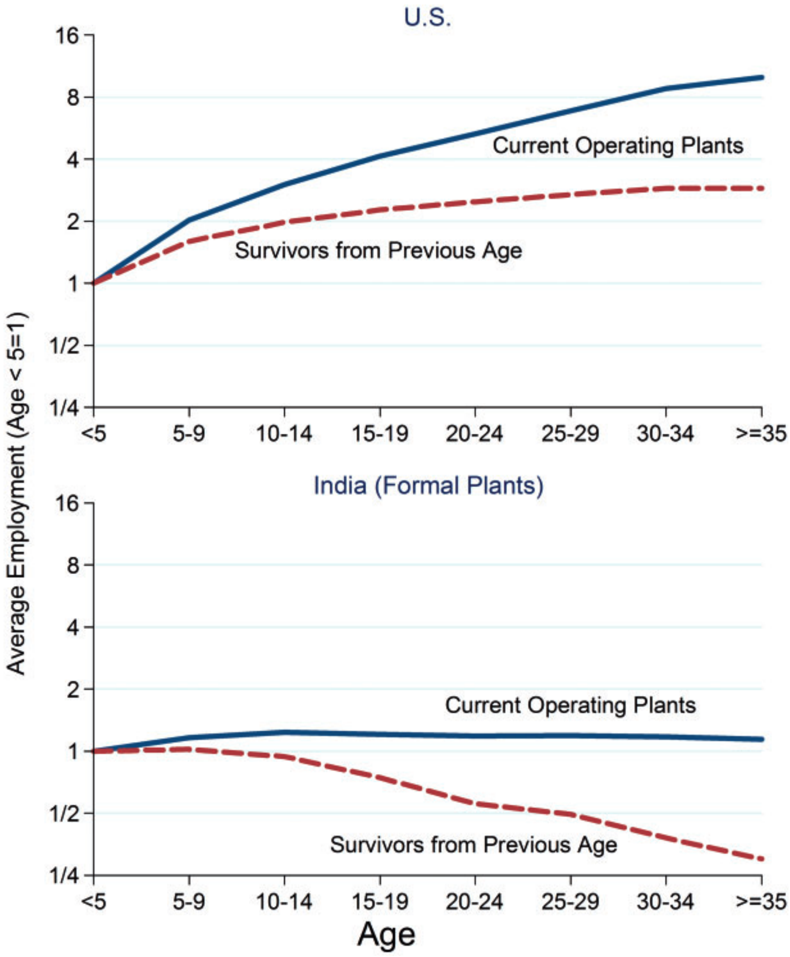

FIGURE VIII

Employment Growth over the Life Cycle

Employment growth with age is imputed from the 1992 and 1997 U.S. Manufacturing Censuses and the 1998–1999 and 2003–2004 Indian ASI. "Survivors from Previous Age" are based on comparing plants that operate in both of the years. "Current Operating Plants" is based on all operating plants, including those who do not survive to the latter year.

Specifically, the plot with the label "survivors from previous age" is computed from the growth of those establishments who survive from one sample to the next. To do this we compare average employment for the 5–9-year-old plants in one year to those same plants when they were age < 5 in the previous sample. We do the same for the age 10–14 plants in one year versus the same plants age 5–9 operating five years earlier, and so on. The U.S. data are from the Manufacturing Censuses of 1992 and 1997, and the Indian data are 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 Indian manufacturing, but we think the ASI evidence is still useful. For comparison Figure VIII also reproduces the growth in average employment shown in Figure IV (the plot with the label "current operating plants.")

According to Figure VIII, in both the United States and in formal Indian plants, survivor growth is lower than overall growth. This suggests that exit is negatively correlated with size in both countries. It actually appears that survivor selection is stronger in India than in the United States. The upshot is 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 United States. Instead, what appears to differ between the countries is the growth of survivors. In the United States, surviving establishments experience substantial growth. In India, incumbent plants shrink with age. This fact points to the anemic growth of survivors in India as the driving force for the flat life cycle in Indian plants. We reiterate that the Figure VIII evidence is not conclusive as we do not have evidence from informal Indian plants.

We end this section by presenting evidence on the life cycle in the manufacturing sectors in other countries. Figure IX presents the average size of manufacturing plants at ages 10–14 and 30–34 (relative to age < 5) in the United Kingdom, Canada, France, Italy, and Spain. Appendix I provides details on how these statistics were calculated. Figure IX also reproduces the numbers from our Mexican, Indian, and U.S. data. The United Kingdom and Canada look similar to Mexico. Spain is somewhere between the Indian and Mexican life cycle. France and Italy are somewhere between Mexico and the United States. Whereas manufacturing plants grow eightfold by age 34 in the United States, the equivalent number in Italy is a factor of 6.5, a factor of 3.5 in France, and only a factor of 2 in the United Kingdom and Canada. Perhaps surprisingly, life cycle growth in the United Kingdom and Canada looks similar to that in Mexico. Although the United States and India are at the top and bottom,

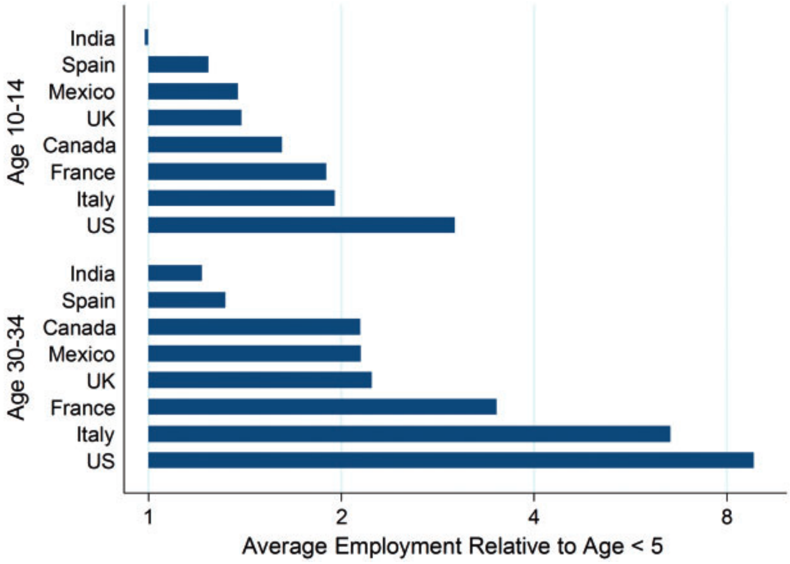

FIGURE IX

Employment Growth over the Life Cycle

Employment growth by age 10–14 and age 30–34 relative to age < 5. Indian data are from plants in the 2009–2010 ASI/NSS. Data for France, Italy, and Spain are for firms in the 2006–2007 Amadeus Database. U.K. data are for plants from 1997–2001 to 2002–2006 in the ARD. Canadian data are for plants from 1999–2001 to 2004–2006 in the Canadian ASM. See Appendix I for additional details.

respectively, the patterns in these other countries are a cautionary reminder that we need more and better evidence to know whether life cycle patterns are strongly related to income per capita across a broad set of countries.

IV. PRODUCTIVITY OVER THE LIFE CYCLE

In this section, we impose more structure on the data to infer how much of the low employment growth of Indian and Mexican plants reflects slow productivity growth with age. Consider a closed-economy version of Melitz (2003). Suppose that aggregate output at time t is given by a constant elasticity of substitution (CES) aggregate of the output of individual establishments:

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

Here i indexes the establishment, a refers to the establishment's age, N_a is the number of establishments of age a (we suppress the subscripts for sector and time), $Y_{a,i}$ is value added of the establishment, 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:

$$(2)\qquad \pi_{a,i} = (1-\tau_{Y_{a,i}})P_{a,i}Y_{a,i} - (1+\tau_{L_{a,i}})wL_{a,i} - (1+\tau_{K_{a,i}})RK_{a,i},$$

where $P_{a,i}$ is the plant-specific output price, $L_{a,i}$ is the plant's labor input, $K_{a,i}$ is 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, transportation costs, size restrictions, labor regulations, and financial frictions.[17] These wedges could also reflect overhead or adjustment costs, which could be technological or policy-related.

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

$$(3)\qquad Y_{a,i} = A_{a,i}K_{a,i}^{\alpha}L_{a,i}^{1-\alpha},$$

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

The equilibrium revenue, labor allocation, and capital-labor ratio of the plant are given by:

$$(4)\qquad P_{a,i}Y_{a,i} \propto \left(\frac{A_{a,i}}{TFP}\cdot\frac{1}{\tau_{a,i}}\right)^{\sigma-1}$$

17. For recent examples see Restuccia and Rogerson (2008), Guner, Ventura, and Xu (2008), Buera, Kaboski, and Shin (2011), Peters (2012), Moll (2012), Midrigan and Xu (2009), and Bhattacharya, Guner, and Ventura (2013).

$$L_{a,i} \propto \left(\frac{A_{a,i}}{TFP}\right)^{\sigma-1}\left(\frac{\bar{\tau}}{\tau_{a,i}}\right)^{\sigma}\left(\frac{1+\tau_{L_{a,i}}}{1+\tau_{K_{a,i}}}\right)^{\alpha\sigma} L \tag{5}$$

$$\frac{K_{a,i}}{L_{a,i}} = \frac{\alpha}{1-\alpha}\cdot\frac{w}{R}\cdot\frac{1+\tau_{L_{a,i}}}{1+\tau_{K_{a,i}}}, \tag{6}$$

where $\tau_{a,i} \propto \frac{\left(1+\tau_{K_{a,i}}\right)^{\alpha}\left(1+\tau_{L_{a,i}}\right)^{1-\alpha}}{1-\tau_{Y_{a,i}}}$, $\bar{\tau}$ is the average value of τ, *TFP* is aggregate TFP, and L is the total number of workers.[18] When the ratio $\frac{\tau_{K_{a,i}}}{\tau_{L_{a,i}}}$ does not vary across plants, the capital-labor ratio does not vary across plants and the allocation of labor is only a function of A and τ. See Hsieh and Klenow (2009) for additional details.

As shown in equations (4) and (5), a plant's revenue and employment are increasing in its productivity A and decreasing in its average revenue product τ. For a given τ, more productive plants have lower costs and therefore charge lower prices and reap more revenue (given $\sigma > 1$). Plants with a higher τ charge higher prices and earn less revenue, for a given level of productivity. To the extent that resource allocation is driven by τ rather than by A, there will be differences in the marginal revenue product of resources across plants. From equations (4), (5), and (6), τ is proportional to the geometric average of the marginal product of labor and capital:

$$\frac{\tau_{a,i}}{\bar{\tau}} \propto \left(\frac{P_{a,i}Y_{a,i}}{K_{a,i}}\right)^{\alpha}\left(\frac{P_{a,i}Y_{a,i}}{L_{a,i}}\right)^{1-\alpha}. \tag{7}$$

We are building on the work of Foster, Haltiwanger, and Syverson (2008), who distinguish between TFPR (revenue TFP, or $\tau_{a,i}$ here) and TFPQ (quantity TFP, or $A_{a,i}$ here). This distinction was key in Hsieh and Klenow (2009) and we use the same idea here. What is different in this article is that we focus on the

18. Aggregate TFP in this model is $\left[\sum_a \sum_{i=1}^{N_a}\left(A_{a,i}\cdot\frac{\bar{\tau}}{\tau_{a,i}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}$ and average revenue product $\bar{\tau}$ is proportional to $\left[\left(\sum_a\sum_{i=1}^{N_a}\frac{1-\tau_{Y_{a,i}}}{1+\tau_{K_{a,i}}}\cdot\frac{P_{a,i}Y_{a,i}}{PY}\right)^{\alpha}\left(\sum_a\sum_{i=1}^{N_a}\frac{1-\tau_{Y_{a,i}}}{1+\tau_{L_{a,i}}}\cdot\frac{P_{a,i}Y_{a,i}}{PY}\right)^{1-\alpha}\right]^{-1}$ where $\frac{P_{a,i}Y_{a,i}}{PY}$ denotes the plant's share of value added. See Hsieh and Klenow (2009) for additional details.

variation of plant productivity $A_{a,i}$ and average revenue product τ with age. Specifically, the *growth* of plant revenue and employment with age in this model depends on the growth of plant productivity with age and the extent to which plant average revenue products change with age.

We need data on PY, K, L, and α to measure plant productivity and average revenue 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 United States 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.

Figure X plots the evolution of plant productivity $A_{a,i}$ over the life cycle. More precisely, Figure X plots life cycle productivity growth relative to aggregate TFP growth.[19] In Mexico and the United States, productivity grows slightly less than employment as plants age. By age 35, productivity grows by a factor of 9.3 in the United States and by a factor of 1.7 in Mexico, whereas employment grows by a factor of almost 10 in the United States and by a factor of 2 in Mexico. In India, productivity at age 35 is 1.5 times higher (compared to age < 5), while employment increases by a factor 1.4 by age 35.

Figure XI plots the geometric mean of the average revenue products of capital and labor ("revenue productivity") over the life cycle. In India, revenue productivity is about 10 percent higher in 35-year-old plants compared to new plants. Older Indian establishments are thus slightly smaller than they would be in an economy where marginal products were equalized across plants by age. In Mexico and the United States, revenue productivity of 35-year-old plants are slightly lower than those of new plants. Because of this, in Mexico and the United States,

19. We infer a plant's relative productivity in a given year using $\frac{A_{a,i}}{TFP} \propto \left(P_{a,i}Y_{a,i}\right)^{\frac{1}{\sigma-1}}\left(\frac{\tau_{a,i}}{\bar{\tau}}\right) \propto \frac{(P_{a,i}Y_{a,i})^{\frac{\sigma}{\sigma-1}}}{K_{a,i}^{\alpha}L_{a,i}^{1-\alpha}}$ (from combining equations (4), (5), and (6)). We use $\sigma = 3$ based on Hsieh and Klenow (2009).

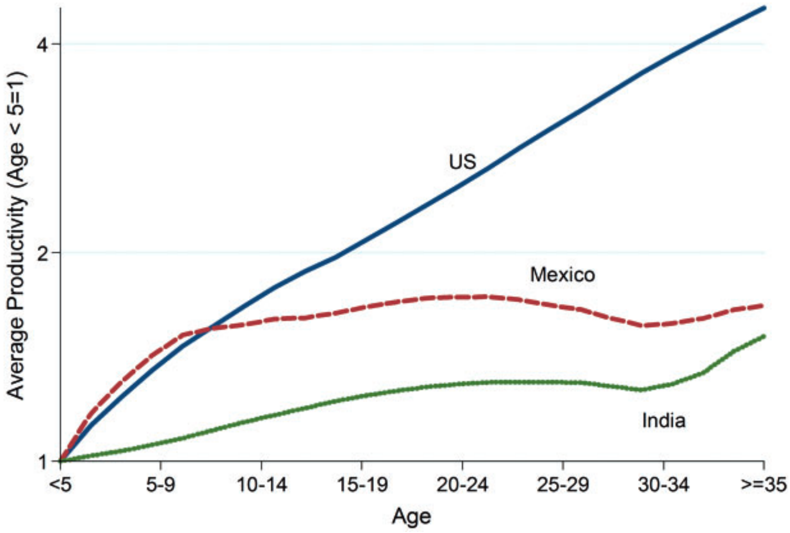

FIGURE X

Productivity over the Life Cycle

Productivity growth imputed from the 1992 and 1997 U.S. Manufacturing Censuses, the 1998 and 2003 Mexican Economic Censuses, and the 1994–1995 to 2010–2011 ASI and NSS in India. Productivity of the youngest age group is normalized to 1 in each country. We compare average productivity per surviving plant relative to aggregate TFP in a later year to average productivity per operating plant relative to aggregate TFP in the same cohort in the earlier year.

employment grows by less with age than is predicted by productivity alone. But the dominant reason for slower employment growth with age in Mexico and India is the slower life cycle productivity growth in these countries.

Why does productivity grow by less in India and Mexico over the plant's life cycle? As a suggestive piece of evidence, Figure XII plots revenue productivity versus productivity in the cross-section for each of our three countries. The average revenue product of capital and labor rises much more steeply with productivity in India and Mexico than in the United States. In India and Mexico, a doubling of establishment productivity is associated with a 50–60 percent increase in the average revenue product of factor inputs. In the United States a doubling of productivity is associated with a 10 percent gap in average revenue products. In the next section, we assess whether this steeper slope of

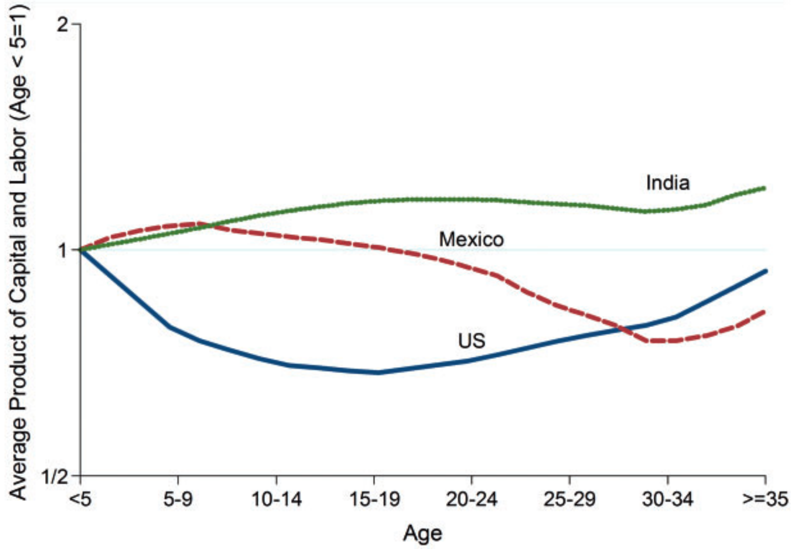

FIGURE XI

Revenue Productivity over the Life Cycle

Growth of the average revenue product of capital and labor in the 1992 and 1997 U.S. Manufacturing Censuses, the 1998 and 2003 Mexican Economic Censuses, and the 1994–1995 and 2010–2011 ASI-NSS in India. For the youngest age, Revenue Productivity is normalized to 1.

revenue productivity with respect to productivity in India and Mexico can explain the low growth of productivity over the life cycle, as well as the implications for aggregate TFP.

V. IMPACT OF THE LIFE CYCLE ON AGGREGATE PRODUCTIVITY

We now try to address two questions. First, how does the life cycle contribute to aggregate productivity differences between India, Mexico, and the United States? Second, can distortions (consistent with the average revenue product data) explain the life cycle patterns in a model with endogenous productivity? We first consider models with exogenous life cycle productivity. Then we consider models in which life cycle productivity is endogenous.[20]

20. Cole, Greenwood, and Sanchez (2012) also construct a quantitative model to fit our facts for India, Mexico, and the United States. In their model financing

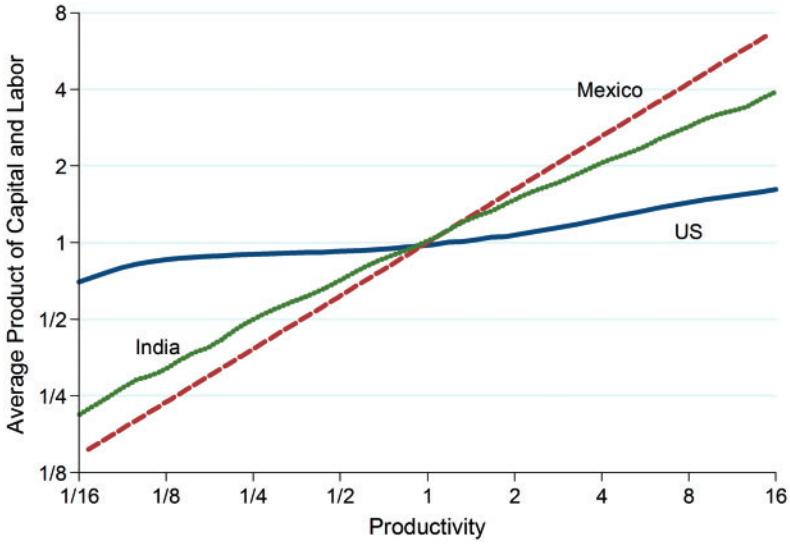

FIGURE XII

Revenue Productivity versus Productivity in the Cross-Section

The average revenue product of capital and labor (τ) and productivity (A) are relative to weighted averages of industry τ and A in each country. Sources: 2010–2011 ASI-NSS (India), 2003 Economic Census (Mexico), and 1992 Manufacturing Census (United States).

In all the models we consider, we assume that incumbent exit rates are high enough that life cycle productivity growth only affects the steady-state level of productivity not the long-run growth rate (see Luttmer 2010). The long-run growth rate is driven by increases in entrant productivity. In these models, we are attempting to quantify the level effect of the life cycle on aggregate productivity. To illustrate, consider the stylized depiction in Figure XIII. In this hypothetical plot, "U.S." incumbent productivity rises much faster than that of successive cohorts of U.S. entrants. In "India" incumbent productivity rises only a little faster than the rate at which entrants improve. As a result, average firm productivity in the cross-section of plants at a point in time will be higher in the "U.S." than in "India." It is this

frictions inhibit incumbent technology adoption in India and Mexico. Akcigit and Peters (2013) pursue the idea that managerial costs account for our empirical patterns.

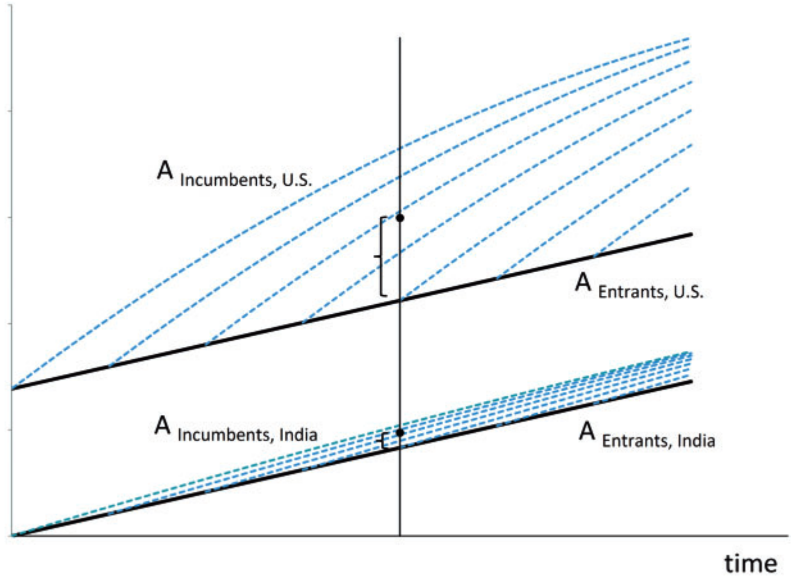

FIGURE XIII
Hypothetical Productivity across Cohorts

level effect—the proportional difference in bracket heights in Figure XIII—that we aim to quantify.

We consider a sequence of simple GE models with monopolistic competitors whose productivity varies over their life cycle. In addition to Melitz (2003), we follow Atkeson and Burstein (2010) in our modeling choices. As detailed in the Online Appendix, we assume:

(i) a closed economy,
(ii) no aggregate uncertainty,
(iii) additively time-separable isoelastic preferences over per capita consumption,
(iv) constant exogenous growth in mean entrant productivity A,
(v) labor as the sole input (including for entry, innovation, and overhead),
(vi) fixed aggregate supply of labor (equal to the population),
(vii) exit rates as a fixed function of a plant's age and A,
(viii) average revenue products (T's) as a fixed function of a plant's age and A.

These assumptions imply two convenient properties about the resulting equilibria:

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

See Luttmer (2010) as well as Atkeson and Burstein (2010), who derive these properties.

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

$$(8)\qquad TFP = \frac{Y}{L} = \left[\sum_a \sum_{i=1}^{N_a} \left(A_{a,i} \cdot \frac{\bar{\tau}}{\tau_{a,i}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}} \frac{L_Y}{L},$$

where $Y_{a,i} = A_{a,i}L_{a,i}$ and $\tau_{a,i} = \frac{P_{a,i}Y_{a,i}}{L_{a,i}} = P_{a,i}A_{a,i}$. Because these models do not have capital, we assume at most a single revenue distortion $\tau_{a,i}$ hitting each plant, with average value $\bar{\tau}$.[21] In equation (8), $\frac{L_Y}{L}$ is the fraction of the labor force working to produce current output. The total workforce is fixed at $L = L_Y + L_R + L_O$ each period. L_Y is the sum of production labor across all plants, 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, and L_O denotes labor used for overhead. It will be useful to express aggregate TFP in equation (8) as the product of average A, varieties, and the share of resources used to produce current output:

$$(9)\qquad TFP = \bar{A} \cdot N^{\frac{1}{\sigma-1}} \cdot \frac{L_Y}{L}.$$

Average firm productivity is $\bar{A} = \left[\frac{\sum_a \sum_{i=1}^{N_a} \left(A_{a,i} \cdot \frac{\bar{\tau}}{\tau_{a,i}}\right)^{\sigma-1}}{N}\right]^{\frac{1}{\sigma-1}}$, and $N = \sum_a N_a$ is the total number of firms (and varieties). In our exercises, we will illustrate the effect of the life cycle on aggregate TFP as well as on the three components in equation (9).

21. In terms of the earlier notation, $\tau_{a,i} = \frac{1}{1-\tau_{Y_{a,i}}}$ and $\bar{\tau} = \frac{1}{\sum_a \sum_{i=1}^{N_a} \frac{P_{a,i}Y_{a,i}}{PY} \frac{1}{\tau_{a,i}}}$.

TABLE II
MODELS WITH EXOGENOUS LIFE CYCLE PRODUCTIVITY

Rows in Tables IV and V	Entry	Entrant quality	τ variation
Row 1	Fixed	Fixed	None
Row 2	Free	Fixed	None
Row 3	Free	Endogenous	None
Row 4	Free	Fixed	Overhead costs
Row 5	Free	Fixed	Adjustment costs
Row 6	Free	Fixed	Revenue taxes

Notes: A refers to firm productivity, and τ to the firm's average product of capital and labor. In all cases there is dispersion of A within and across ages, and exit is exogenous and varies by age and productivity.

V.A. *Exogenous Life Cycle Productivity*

We start by considering models with exogenous life cycle productivity. Firms in a given entering cohort have heterogeneous productivity on entry to fit the entrant productivity distribution in the United States.[22] As firms age, their productivity grows exogenously at a common, age-specific rate. Exit rates are exogenous but depend on age and productivity as in the United States. We first calculate aggregate TFP from equation (9) using U.S. A by age. We then separately calculate aggregate TFP assuming Indian and Mexican levels of A by age.

Table II lists the exogenous life cycle productivity models we consider. Table III lists the parameter values that apply to all cases. The results for India are shown in Table IV, and for Mexico in Table V. Based on equation (9), the columns present aggregate TFP, average firm productivity, the number of varieties, and production workers relative to the workforce.

The first case assumes the flow of entrants is fixed over time. It further assumes that τ does not differ across firms. In this case, going from the United States to Indian and Mexican life cycle A growth lowers aggregate productivity by 25% in India and 18% in Mexico. Because entry is fixed, the mass of firms is fixed and does not respond to the life cycle. Thus the change in aggregate TFP is the same as change in average firm productivity. To put the 25% decline in aggregate TFP in India into perspective, aggregate TFP in Indian manufacturing is about 62% below that in the

22. 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.

TABLE III

Parameter Values for Exogenous Life Cycle Productivity

Parameter	Definition	Value or target
σ	Elasticity of substitution between varieties	3
γ	Coefficient of relative risk aversion	2
ρ	Discount rate	Annual real interest rate of 5%
N	Maximum life span of a firm	100 years (20 periods; 1 period = 5 years)
g_e	Growth rate of mean entrant *A*	2.1% per year for all models (U.S. average TFP growth)
A_a	Productivity by age	Set to match productivity by age data *in each country*
σ_e	Std. dev. of entrant log productivity	1.01 to match productivity dispersion of age 0–5 U.S. plants
δ_a	Exit by age, conditional on productivity	U.S. exit rates by 5-year age group
$\delta_{a,i}$	Exit by productivity, conditional on age	U.S. semi-elasticity of exit w.r.t. plant productivity
f_e	Entry costs (in terms of labor)	Average workers per plant in the U.S.
$\tau_{a,i}$	Average products by productivity level	Set to match U.S. elasticity of average products w.r.t. productivity

Notes. Average products vary with productivity only in the presence of overhead costs, adjustment costs, or revenue taxes (rows 4–6 in Tables II, IV, and V). See Section V and the Online Appendix for more detail.

United States (Hsieh and Klenow 2009). So slower life cycle productivity growth might account for about 30% of the aggregate TFP difference (ln(0.75)/ln(0.38) & 0.30).

The previous calculation assumed no response of entry to life cycle growth. In the data, average plant size is smaller in India and Mexico than in the United States. Figure XIV plots the employment distribution by plant size in the three countries. As exit and entry rates are no lower in India and Mexico, their mass of entrants must be bigger, even in per worker terms. 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. Entrants, facing less competition from efficient incumbents, enjoy higher discounted profits, all else held constant. Entry therefore increases to

TABLE IV

Percent Change from U.S. to Indian Life Cycle in Models with Exogenous Life Cycle Productivity

Cases	Aggregate TFP	Weighted average A	Entry	Workers/ workforce
Baseline	−25.1	−25.1	0	0
Free entry	−23.3	−25.1	+11.3	−3.6
Endogenous entrant quality	−28.9	−46.4	+100.7	0
Overhead costs	−16.5	−24.8	+26.1	−2.6
Adjustment costs	−22.3	−24.6	+12.5	−3.5
Revenue taxes	−23.4	−25.1	+9.9	−3.2

Notes. Table entries are % changes when going from U.S. to Indian productivity (A) by age. Aggregate TFP is the product of three terms ($TFP = \frac{Y}{L} = \bar{A} N^{\frac{1}{\sigma-1}} \frac{L_Y}{L}$), weighted average A, a variety term involving the mass of firms, and the fraction of the population producing current output (as opposed to supplying overhead labor or generating entry).

TABLE V

Percent Change From U.S. to Mexican Life Cycle in Models With Exogenous Life Cycle Productivity

Cases	Aggregate TFP	Weighted average A	Entry	Workers/ workforce
Baseline	−18.2	−18.2	0	0
Free entry	−16.7	−18.2	+7.8	−2.5
Endogenous entrant quality	−23.5	−42.4	+101.5	0
Overhead costs	−13.0	−17.9	+14.9	−2.1
Adjustment costs	−16.0	−18.0	+9.3	−2.7
Revenue taxes	−16.8	−18.2	+6.7	−2.2

Notes. Table entries are % changes when going from U.S. to Mexican productivity (A) by age. Aggregate TFP is the product of three terms ($TFP = \frac{Y}{L} = \bar{A} N^{\frac{1}{\sigma-1}} \frac{L_Y}{L}$), weighted average A, a variety term involving the mass of firms, and the fraction of the population producing current output (as opposed to supplying overhead labor or generating entry).

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.

We now consider what happens with endogenous entry when moving from the U.S. to Indian and Mexican life cycle growth. We assume that in equilibrium, the expected discounted value of profits for entrants is equal to the entry cost. This formulation of the free entry condition, from Hopenhayn (1992), assumes that potential entrants only observe their productivity after they pay the entry cost (we relax this assumption shortly). We denominate

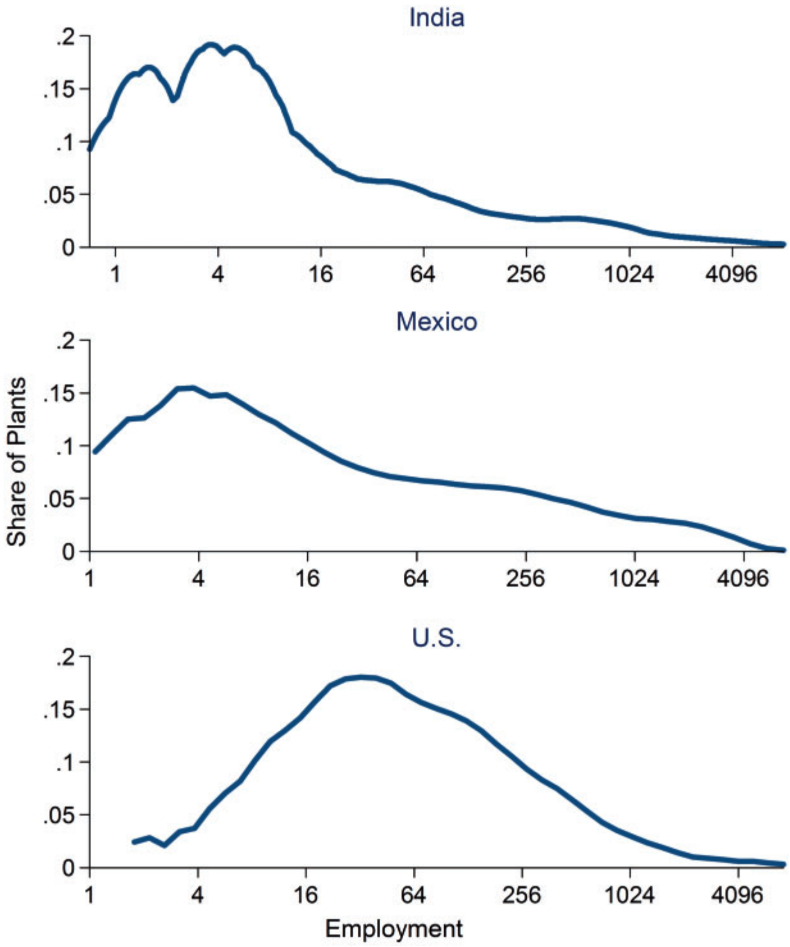

FIGURE XIV

Distribution of Establishments by Employment

Sources: 2010–2011 ASI-NSS (India), 1998 Economic Census (Mexico), and 1997 Manufacturing Census (United States). Plants are weighted by the per-plant value-added share of each four-digit industry.

entry costs in units of labor in light of Bollard, Klenow, and Li (2013). We set the level of entry costs to fit the average plant size in the United States.[23] We then calculate aggregate TFP with

23. Average employment per plant in the United States is 45 workers (see Table I and Figure XIV).

Indian and Mexican life cycle productivity growth, allowing entry to endogenously respond.

The second row of Tables IV and V presents the endogenous entry case. Intuitively, there will now be two effects. First, as in the baseline case, average firm A falls by construction (column (2)). What is new is that entry rises (column (3)): by 11% in India and 8% in Mexico. The net effect on aggregate TFP is still negative, at -23% in India and -17% in Mexico. Even with our low substitutability ($\sigma = 3$) and therefore strong love of variety, 11% more variety in India lifts aggregate TFP less than 6%. The additional entry diverts some labor from goods production, lowering the share of people producing current output (column (4)) by 3.6% in India and 2.5% in Mexico. On net the variety response does offset some of the TFP loss from lower life cycle productivity growth, but it is not a major offset. Fattal Jaef (2012) obtains a similar result 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 with the same quality of entrants requires twice as much entry labor. If there are instead diminishing returns to entry, then the outcome would be different. We provide a specific example shortly. 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, textiles, 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 Appendix II inspired by his work.

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 United States. The standard deviation of log A across age 0–4 plants is 1.27 in India and 1.46 in Mexico, versus 1.01 in the United States.[24] Greater entrant productivity dispersion in India and Mexico could be a by-product of greater entry there. To illustrate, suppose there is a fixed mass of potential entrants

24. The U.S. number is for 1997. In 1987 and 1992, the standard deviation of ln TFPQ in the United States is 0.87 and 0.88, respectively. The Mexican number is for 1998 and for 1994–1995 for India.

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.

To consider the case with endogenous entrant quality, we need to know the distribution of potential entrants as well as the entry cost. We continue to calibrate the entry cost to match average employment per plant in the United States. We calibrate the mass of potential entrants to match the A dispersion in India when we go from U.S. life cycle A to Indian life cycle A. The implied entry cost from this exercise is much smaller because the zero profit condition only holds for the marginal entrant.

The third row of Tables IV and V shows the effect, under endogenous entrant quality, of moving from U.S. to Indian or Mexican productivity with age. As in the previous two cases, lower life cycle growth directly lowers average A. As before, entry increases—variety more than doubles when moving from the U.S. life cycle to the Indian and Mexican life cycles. Marginal entrants are lower productivity firms, whereas our previous case assumed that marginal entrants were no different from the average entrant. Here, more entry (i) lowers the average A among entrants, and (ii) increases the dispersion of A among entrants. Previously both were held fixed. Taking into account the slower life cycle productivity growth and the lower quality of entrants, the result is 46% lower average plant productivity (versus the 25% fall with a constant quality of entrants) in the Indian case. Because the calibrated entry cost is now extremely small to explain why the low A marginal entrant has zero profits, the surge of entry in this counterfactual requires little extra labor devoted to entry. The net effect on overall TFP in the Indian simulation, including the variety gain, is -29%.

We have so far assumed no τ variation across firms. But we reported earlier that τ varies with productivity in all three countries (Figure XII). We now consider the effect of productivity growth with age in models with τ variation. We entertain three interpretations of τ: overhead costs, adjustment costs, and taxes.[25] In all three cases, we assume that entry is endogenous

25. Bartelsman, Haltiwanger, and Scarpetta (2012) model τ as coming from overhead costs, and Asker, Collard-Wexler, and De Loecker (forthcoming) and Midrigan and Xu (2009) model τ as arising from adjustment costs.

but revert to assuming the zero profit condition holds in expectation for all entrants.

We begin by assuming that τ reflects overhead costs. If overhead costs do not vary across firms and average 14% of employment as in Barteslman, Haltiwanger, and Scarpetta (2013), then we cannot come close to generating the productivity dispersion seen among entering plants in the United States (a standard deviation of 1.01 in $\ln A$). This is because if overhead costs are big and common to all firms, then smaller firms should shut down. We thus allow overhead costs to increase with firm productivity, though not of course with firm labor. (We assume that the marginal value of production labor is equalized across firms.) This seems plausible—more advanced technology could require bigger overhead costs—and it can explain why so many small firms operate. We choose the maximum slope of overhead costs such that we can match U.S. entrant productivity dispersion. In the presence of these overhead costs, we see the effect of going from U.S. productivity by age to Mexican and Indian productivity by age in row four of Tables IV and V. The aggregate TFP losses are 16.5% in India and 13% in Mexico—more modest than without overhead costs (23% and 17%) because there is a bigger variety offset here. When overhead costs are low for low-productivity firms, slower productivity growth with age has a bigger effect on entry.

Row five of Tables IV and V illustrate the case when we interpret τ as adjustment costs. Here, we assume that firm productivity growth is stochastic and half of the firm's labor is predetermined one period ahead (prior to the realization of the productivity shock). The impact on entry is smaller here, so the results with adjustment costs are closer to the baseline case with no adjustment costs than to the case with overhead costs.

The last row in Tables IV and V considers the case when we interpret τ as reflecting productivity-dependent tax rates on firm revenue. The effect of lower life cycle productivity growth on aggregate TFP here is similar to the case that abstracts from τ variation (second row).

To recap, going from U.S. to Indian or Mexican exogenous life cycle productivity growth lowers aggregate TFP by between 13% and 24% depending on the model.

V.B. Endogenous Life Cycle Productivity

In the preceding simulations, life cycle growth arose exogenously. In this subsection, we simulate models in which life cycle productivity growth is endogenous to innovation by firms. We assume that the marginal cost of innovation is the same in all countries and examine the consequence of lower marginal returns to innovation. To impose discipline on how much the marginal return to innovation might differ between India and Mexico versus the United States, we interpret the variation in τ in the data as reflecting variation in revenue tax rates.[26] With this interpretation of τ, the steeper τ by A slopes in India and Mexico (Figure XII) suggests that the marginal return to innovation is lower in India and Mexico.[27] We then simulate the effect of a lower marginal return to innovation implied by a steeper τ by A slope on life cycle productivity growth and aggregate TFP.

To implement this model, we also need to parameterize the cost of innovation. We adapt the cost specification of Atkeson and Burstein (2010).[28] Here incumbents choose the probability q of taking a proportional step up versus down in their A. (We use Atkeson and Burstein's step size, chosen to match the 25 percent standard deviation of employment growth of large plants in the United States.) The cost of this investment is

$$(10) \qquad C\left(A_{a,i}, q_{a,i}\right) = hA_{a,i}^{\sigma-1} exp\left(b \cdot q_{a,i}\right).$$

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 values of the "scale" and "convexity" parameters h and b to roughly fit A by age in the United States while generating the τ by A slope seen in the U.S. with

26. Of course we do not literally mean tax rates, as τ can also reflect forces such as contractual frictions in hiring nonfamily labor, higher tax enforcement on larger firms, financial frictions, difficulty in buying land or obtaining skilled managers, and costs of shipping to distant markets. See Appendix II for models of two specific barriers, namely, managerial costs and transportation costs that generate variation in revenue productivity (τ) in the data.

27. In a one-period model the marginal increase in profits from a marginal increase in A is proportional to $\left(\frac{A}{\tau}\right)^{\sigma-1}$, where τ is the revenue tax rate.

28. For simplicity we revert to zero expected profits for all entrants in this subsection.

revenue tax rates.[29] See Figure XV. See Table VI and the Online Appendix for details on how we implemented this.

Fixing the innovation cost function parameters and other parameters at U.S. baseline values, we evaluate the effect of moving from the τ by A slope in the United States (0.09) to the slopes seen in India (0.50) or Mexico (0.66). Figures XVI and XVII present the resulting model versus data life cycles for India and Mexico. In India, rising tax rates have some success in replicating the slow life cycle productivity growth there, accounting for 30% of the difference in cumulative growth from age 0–4 to age 30–34 (expressed as relative log points). In Mexico, in contrast, rising tax rates overexplain the sluggish life cycle there, accounting for 153% of the difference in cumulative life cycle growth.

Table VII shows the effect on aggregate TFP of increasing the slope of the tax rate with A. This has four effects. First, rising tax rates with A discourages innovation and lowers life cycle productivity growth (as shown in Figures XVI and XVII). Second, greater tax rate dispersion generates misallocation, which lowers aggregate TFP for a given distribution of productivity (as in Hsieh and Klenow 2009). These two effects lower average A by 40% in India and 56% in Mexico (column (2)), which is larger than in the exogenous life cycle growth case because of the effect of greater misallocation on TFP (which was not present in the exogenous growth simulations where we kept the τ versus A slope fixed at the U.S. slope.) Third, firms must invest labor in R&D to achieve life cycle growth, so less life cycle growth frees up R&D labor. Fourth, as in the exogenous growth case, entry increases when life cycle productivity growth declines. The net effect of these four effects is to lower aggregate TFP by 36.5% and 53% (in India and Mexico, respectively).

It is worth contrasting our results with Atkeson and Burstein (2010). They find second-order losses from trade barriers with endogenous incumbent productivity in an otherwise Melitz-style model. In their setting, trade barriers undermine the incentive of incumbents to innovate. But such trade barriers also

29. We do not report results with overhead costs or adjustment costs because they cannot come close to mimicking the steep τ by A slopes seen in India and Mexico. With overhead costs the problem is the firms would rather shut down than endure high overhead costs. Even entirely predetermined labor over a five-year period, meanwhile, generates only a mild upward slope in revenue productivity with respect to productivity, given that most firm productivity variation is persistent over time.

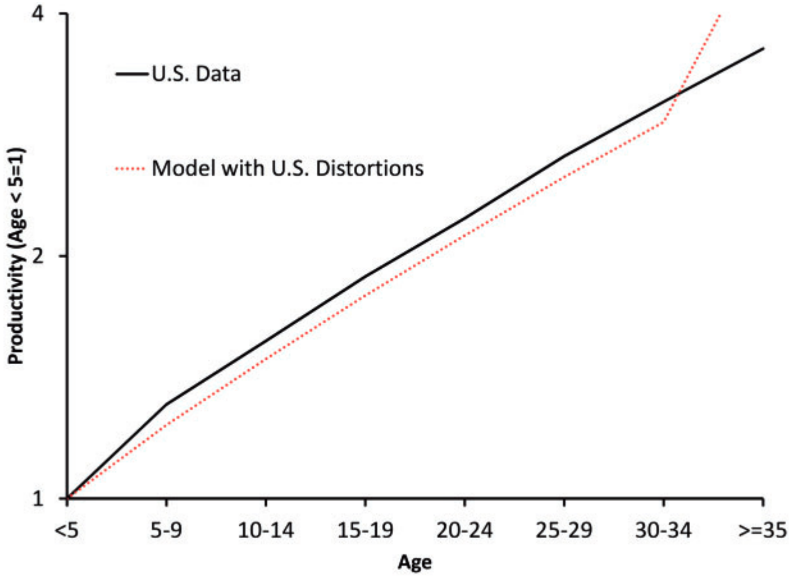

FIGURE XV

Productivity by Age in the United States, Data and Models

TABLE VI

PARAMETER VALUES FOR ENDOGENOUS LIFE CYCLE PRODUCTIVITY

Parameter	Definition	Value or target
h	Level parameter in the R&D cost function	Set with b to match U.S. productivity by age group
b	Convexity parameter in the R&D cost function	Set with h to match U.S. productivity by age group
$\tau_{a,i}$	Average products by productivity level	Set to match elasticity of average products w.r.t. productivity *in each country*

Notes. The following parameters are the same as in the simulations with exogenous productivity by age (see Table III): $\sigma = 3$ (the elasticity of substitution between varieties); $\gamma = 2$ (the coefficient of relative risk aversion); ρ (the discount rate) to yield an annual real interest rate of 5%; $N = 100$ (maximum life span of a firm in years); $g_e = 0.021$ (growth of mean entrant productivity); $A_{0,i}$ (entrant productivity dispersion) to match productivity dispersion of young U.S. plants; δ_a (exit rate by age conditional on productivity) to match U.S. exit by age data; $\delta_{a,i}$ (exit rate by productivity for a given age) to match U.S. semi-elasticity of exit w.r.t. productivity; and f_e (entry costs in terms of labor) to match average employment per plant in the United States. Average products vary with productivity due to revenue taxes. Entry is free, productivity growth is stochastic and endogenous, and there are no overhead costs or adjustment costs. See Section V and Appendix I for more detail.

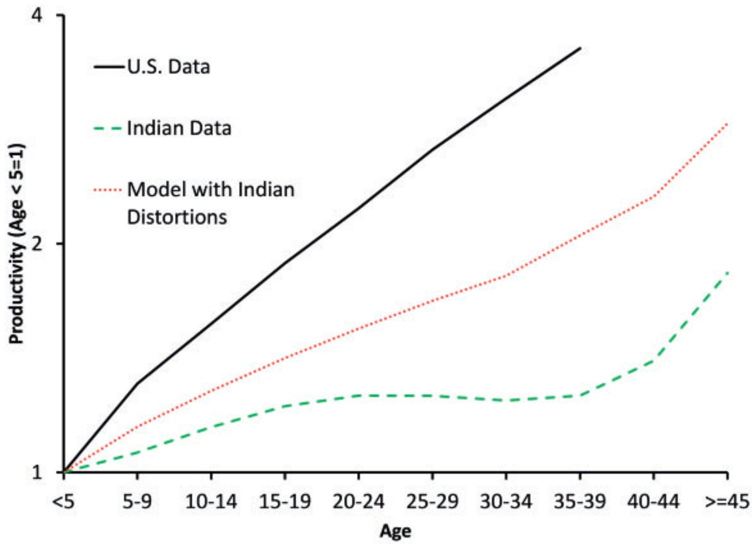

FIGURE XVI
Productivity by Age in India, Data and Models

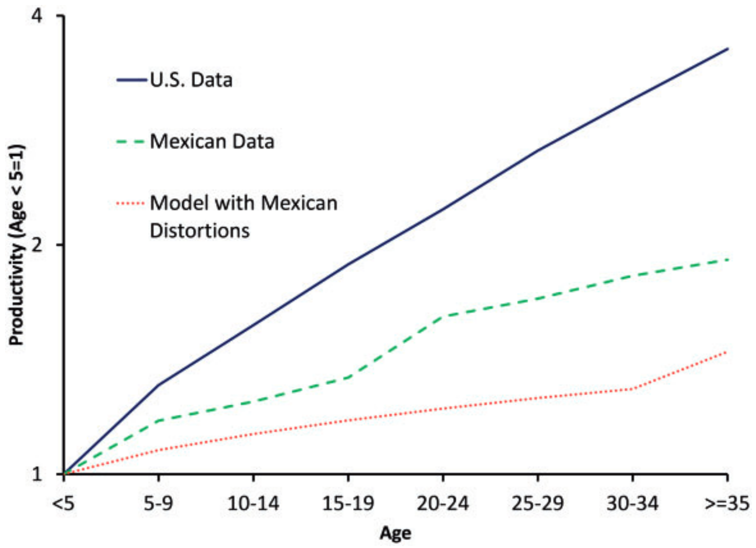

FIGURE XVII
Productivity by Age in Mexico, Data and Models

TABLE VII

PERCENT CHANGE FROM THE U.S. TO INDIAN AND MEXICAN AVERAGE PRODUCTS IN MODELS WITH ENDOGENOUS LIFE CYCLE PRODUCTIVITY

Cases	Aggregate TFP	Weighted average A	Entry	Workers/workforce
India	−36.5	−39.7	+14.3	−1.5
Mexico	−53.0	−55.7	+16.4	−1.3

Notes. Table entries are % changes when going from U.S. to Indian average products (τ) by age. Aggregate TFP is the product of three terms ($TFP = \frac{Y}{L} = \tilde{A} N^{\frac{1}{\sigma-1}} \frac{L_Y}{L}$): weighted average A, a variety term involving the mass of firms, and the fraction of the population producing current output (as opposed to supplying overhead labor, generating entry, or doing research).

stimulate entry. The benefits of additional variety almost exactly offset the slower life cycle growth in their calculations. We obtain big net losses, in contrast, because the incumbent distortions we consider are large. This is driven by the steeply increasing revenue productivity data with respect to productivity we observe in India and Mexico. We, too, find trivial aggregate TFP losses if we start from an economy with no incumbent distortion (i.e., no slope of τ by A) and move to a small slope (e.g., a 0.01 elasticity of τ by A).

Finally, it is worth asking whether big TFP losses would occur under other, nontax explanations for revenue productivity dispersion in India and Mexico. Motivated by Peters (2012), we explored variable price-cost markups in particular. In the U.S. baseline, we kept markups the same across firms but did allow tax rates to vary with productivity. In the Indian and Mexican counterfactuals, we kept the tax schedule the same as in the United States, but allowed markups to vary—starting at 0% for the lowest productivity firm and rising to 50% (the monopoly markup) for the highest productivity firm. Even this extreme markup variation only increased the τ by A slope from 0.09 (the U.S. baseline) to 0.12. (The τ by A slope is 0.50 in India and 0.66 in Mexico.) Rising markups over this range implied faster life cycle productivity growth in the counterfactuals compared to the U.S. baseline. The reason is going from a suboptimal to profit-maximizing markup is further incentive to invest in R&D.

To recap, if we interpret the variation in τ in the data as variation in tax rates, the steeper higher τ by A slope in India and Mexico can generate the slower life cycle productivity growth in these countries in a simple model of endogenous innovation. But it should be clear that this is just a first pass at explaining the differences in firm dynamics in India and Mexico versus the

United States. For example, we assumed that the innovation cost function is the same in all countries, but the marginal cost of innovation could be higher in India and Mexico. Additional evidence on this would be useful.

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 United States 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 article, we took up a 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, resulting in lower productivity of the average plant in poor countries. A key fact consistent with this interpretation is that manufacturing plants in the United States grow with age while manufacturing plants in Mexico and India exhibit little growth in terms of employment. 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 percent drop in aggregate TFP.

An important question left for future research is identifying the specific barriers facing larger plants in India and Mexico. In an earlier version (Hsieh and Klenow 2012) we provided suggestive evidence on a number of possible barriers, such as contractual frictions in hiring nonfamily labor, higher tax enforcement on larger firms, financial frictions, difficulty in buying land or obtaining skilled managers, and costs of shipping to distant markets. In this spirit, Table VIII shows that most plants are informal in both India and Mexico, with a majority of employment at informal establishments in India.

TABLE VIII

Informal Workers and Establishments in India and Mexico

	Unpaid workers		Informal establishments	
	% Workers	% Establishments	% Workers	% Establishments
India				
1989–90	73.4	94.2	80.5	99.4
2010–11	54.2	90.8	78.5	99.4
Mexico				
1998	10.2	55.0	14.8	75.6
2008	29.7	60.0	30.4	87.1

Notes. "% Workers" is the percent of unpaid workers or workers in informal establishments as a share of total workers. "% Establishments" is percent of establishments with only unpaid workers or that are informal as share of total number of establishments. Informal establishments are defined as establishments not formally registered (in India) or not registered with the Social Security Agency (in Mexico).

Appendix II briefly sketches models of two specific barriers, namely, managerial costs and transportation costs. Akcigit and Peters (2013) pursue the managerial explanation in more theoretical and quantitative detail. We hope to investigate these potential driving forces systematically in future work.

Appendix I: Data Sets

In this appendix we do two things. First, we compare the information provided by the ASI-NSS data with data from India's Labor Force Survey and Economic Census, respectively. Second, we discuss the data used for the United Kingdom, Canada, France, Spain, and Italy presented in Figure IX.

We checked that the total number of workers in the combined ASI-NSS data set is consistent with data on manufacturing employment from India's Labor Force Survey (Schedule 10 of the NSS). The two years for which we have data for both data sets are 1999–2000 and 2004–2005. According to the establishment level data in the ASI-NSS, the total number of workers in the manufacturing sector was 37 million in 1999–2000 and 45 million in 2005–2006. When we use the labor force survey, we get 37 million workers in manufacturing in 1999–2000 and 46 million in 2005–2006.

Next, we compare data from the ASI-NSS with the information provided from India's Economic Census. We have the microdata from the 2005 Economic Census so we compare this data with the 2005–2006 ASI-NSS. The Economic Census is a complete enumeration of all economic establishments, but it reports only total employment; it contains no data on output or value added. In the absence of output data in the census, we cannot compute the same weighted value-added share-weighted average across four digit industries that we present in the rest of the article (e.g., Figure XIV). We instead weight each establishment by its employment in Figure A.I, which presents the size distribution of employment by establishment size in manufacturing establishments in the 2005 census and the 2005–2006 ASI-NSS. As can be seen, the two distributions are not identical. There is more employment in very small establishments (with one and two employees) in the census. Nonetheless, the distribution of employment by establishment size—in particular, the dominance of employment by small establishments—is similar in the two data sets.

We now turn to a description of the data used to estimate the life cycle of employment in the United Kingdom, Canada, France, Italy, and Spain. The U.K. data are from the Annual Respondents Database (ARD) from 1997 to 2006. The ARD is an annual census of large manufacturing establishments and a survey of smaller establishments conducted by the U.K. Office for National Statistics. We focus on cohorts born before 2001. In 2002, there was a change in the corporate tax law that set the corporate income tax rate to 0 for the first £10,000 of earnings. This tax change may have led to creation of new incorporated establishments that previously were registered as self-employed businesses. We follow cohorts defined in five-year age bins in each year from 1997 to 2001 over five years (from 1997 to 2002, 1998 to 2003, 1999 to 2004, 2000 to 2005, and 2001 to 2006). Since we did not have direct access to the data, the estimates of cohort growth give equal weight to each establishment (i.e., we did not weight by industry value added as we did for India, Mexico, and the United States). We then take an average of the implied growth rates by age for each five-year period as the average employment growth by age.

The Canadian data are from tabulations from the Canadian Annual Survey of Manufacturing (ASM) reported in Kueng and Yang (2014). Kueng and Yang use a random stratified sample of roughly 1,500 plants in the Canadian ASM from 1999 to 2006. They report the average size of manufacturing plants for cohorts defined in five-year age bins for each year. Their estimates use

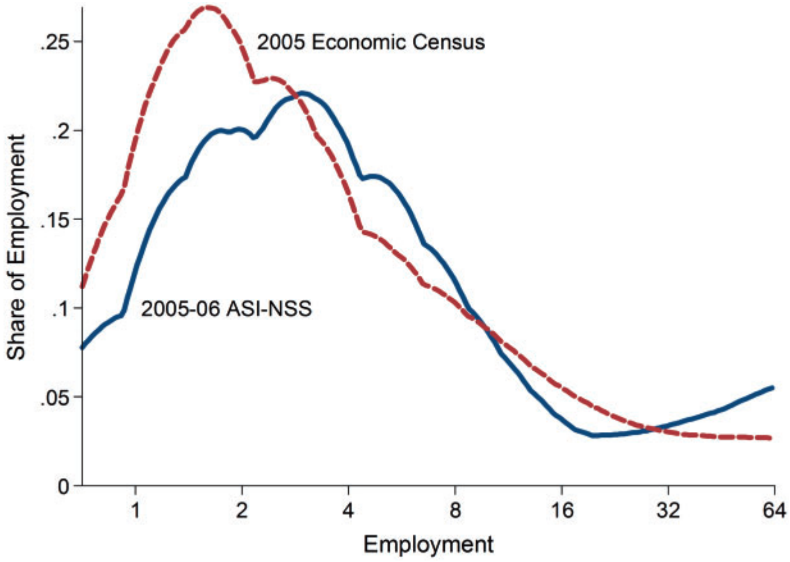

FIGURE A.I

Distribution of Employment by Establishment Size (2005 Census versus 2005–2006 ASI-NSS)

the sampling weights to obtain population means but do not weight by industry value added. From their estimates, we can follow cohorts defined in five-year age bins in each year from 1999 to 2001 over five years (from 1999 to 2004, 2000 to 2005, and 2001 to 2006). As with the British data, we compute the implied growth rate by age for each five-year period as the average employment growth by age.

The data for France, Italy, and Spain are from the Amadeus database. These are the only Amadeus countries in Western Europe with a usable manufacturing sample, but there remain important limitations of the Amadeus data for France, Italy, and Spain. First, the unit of observation is a registered firm (not an establishment). Second, the database provides employment for only 40–50% of the sample, although it provides the wage-bill for most of the firms (roughly 90% of the sample). For firms with missing information on employment, we impute employment from the coefficients of a regression of log employment on a fourth-order polynomial in the log wage-bill and firm age (from the sample with nonmissing data on the wage-bill and employment). Third, the sample appears to be most complete in 2006 and 2007. Specifically, when we estimate the exit rate from 2006 to 2007 by age, we get a reasonable estimate (around 10%). In contrast, estimates of the "exit rate" on the sample prior to 2006 yield negative exit rates, which suggests that coverage of the data was improving leading up to 2006.

Using the Amadeus data for France, Italy, and Spain, we calculate average employment of each cohort, this time defined as one-year age bins, in 2006. We calculate the growth rate of average employment of each one-year cohort from 2006 to 2007. Based on the growth rate of each cohort from 2006 to 2007, we then calculate the implied life cycle growth of firms between the ages 0 to 4 and 10–14, and between 0 to 4 and 30–34, respectively. The results are shown in Figure IX, alongside the same statistics for Canada, India, Mexico, the United States, and the United Kingdom.

Appendix II: Managerial and Transportation Costs

Here we sketch two models that endogenously generate a positive elasticity of average revenue 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 CES 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. (2013) 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 United States (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

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

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

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

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

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

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

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.

Transportation Costs

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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Supplementary Material

An Online Appendix for this article can be found at QJE online (qje.oxfordjournals.org).

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