CSAE WPS/2010-05

On the Evolution of the Firm Size Distribution in an African Economy [1]

Justin Sandefur[2]

Abstract

The size of the informal sector is commonly associated with low per capita GDP and a poor business environment. Recent episodes of reform and growth in several African countries appear to contradict this pattern. From the mid 1980's onward, Ghana underwent dramatic liberalization and achieved steady growth, yet average firm size in the manufacturing sector fell from 19 to just 9 employees between 1987 and 2003. I use a new panel of Ghanaian firms, spanning 17 years immediately post-reform, to model firm dynamics that differ markedly from well-established 'stylized facts' in the empirical literature from other regions. In contrast with American and European firms, entry of new firms and selection on observable characteristics, rather than within-firm growth, dominates industrial evolution in Ghana.

1. Introduction

The size of the informal sector is commonly associated with low per capita GDP and a poor business environment. Market deregulation (Besley and Burgess, 2004; Botero, Djankov, La Porta, Lopez de Silanes, and Shleifer, 2004; de Soto, 1989), enforcement of property rights (Beck, Demirgüç-Kunt, and Levine, 2003; Kumar, Rajan, and Zingales,

[1] I am grateful to Professor Nicholas Nuamah and Tony Krakah of the Ghana Statistical Service (GSS) for their assistance accessing the National Industrial Census; Moses Awoonor-Williams for organizing various aspects of the survey data collection; Luis Cabral and José Mata for assistance reproducing their earlier results; Ernest Aryeetey, Chris Woodruff and seminar participants at the IZA/WB Conference on Employment and Development for comments; and to my supervisor Francis Teal for consistent input. This document is an output of research funding from the UK Department for International Development (DFID) as part of the iiG, a research programme to study how to improve institutions for pro-poor growth in Africa and South-Asia. The views expressed are not necessarily those of DFID.

[2] Centre for the Study of African Economies, Dept. of Economics, Oxford University. Tel. +44 (0)1865 284 787, justin.sandefur@economics.ox.ac.uk.

1999), and low rates of taxation and bribe extraction are commonly thought to contribute to the emergence of larger, formal enterprises.

The recent track record of several African economies calls these patterns into question. Beginning in the mid 1980s, Ghana launched one of the most ambitious structural adjustment programs in Africa, abolishing price controls, opening capital markets, slashing tariffs, and eventually privatizing the majority of state owned enterprises. These reforms ushered in a period of sustained economic growth, averaging 4.7% per annum from 1984 to 2004 (Aryeetey and McKay, 2007). Yet, as I attempt to document below, over this same period Ghana saw a rapid increase in the relative size of the informal sector, and a secular decline in the average size of industrial activity. Furthermore, this pattern seems to be common across sub-Saharan Africa. During the 1990s, all of the economies for which comparable employment data is available (Cote d'Ivoire, Ghana, Uganda, Kenya and Tanzania) posted slow but positive growth in per capita GDP, and all underwent substantial market-oriented reforms in the 1980s and early 1990s. Nevertheless, all of these economies saw substantial increases in the proportion of the non-agricultural labor force working in the small-scale or informal sector (Kingdon, Sandefur, and Teal, 2006).

This paper uses data from the manufacturing sector in Ghana to investigate the determinants of this trend in detail. I study the evolution of the firm size distribution in Ghana from 1987 to 2003. The main contribution of the paper is to establish two significant departures from well-documented, international 'stylized facts'. Both of these departures highlight the overwhelming importance of firm entry and selection, and the irrelevance of within-firm growth, in understanding industrial evolution in Ghana. In contrast, much previous research on firm dynamics in Africa, by focusing primarily on cross-sections or tracking a fixed panel of existing firms, has systematically overlooked the unique patterns of firm entry and selection that appear to distinguish Africa's industrial development.[3]

Seen in isolation, the recent influx of microenterprises in Ghana could be viewed as either the harbinger of future industrial dynamism, or a sign that formal sector is in relative decline. The firm dynamics documented here provide little basis for optimism. Based on existing patterns of firm growth and survival, there is no sign that current cohorts of new firms contain the seeds of future large-scale enterprises.

The rest of the paper is organized as follows. The next section presents the two primary data sources used in the analysis: two rounds of an industrial census and a

[3]The firm-level panel studies funded by the World Bank through the Regional Program on Enterprise Development (RPED), and subsequent cross-sectional Investment Climate Assessment (ICA) surveys are prime examples of frequently-used data sets that have contributed to this blindspot regarding firm entry. Notable exceptions include recent work on Ethiopia, using firm census data (Shiferaw and Bedi, 2009).

12-year panel survey of a sample of firms. Section 3 relies on graphical analysis to document the first significant finding of the paper: the dominance of selection over within firm growth in explaining the apparent life-cycle of firms, counter to existing evidence from Europe and elsewhere. Section 4 models the distribution dynamics in Ghanaian manufacturing using a simple, first-order, homogenous Markov chain. The Markov model allows me to recover entry rates, and to place overall patterns of job creation and reallocation in a comparative international context. Section 5 turns to the underlying determinants of this trend toward small-scale employment, and the apparent failure of the common association between liberalization and large scale development. I test the importance of credit constraints in explaining the low rates of firm growth at various points in the size distribution. Results suggest that credit market failures place a significant drag on growth among small firms, but the relaxation of all such constraints would be insufficient to overcome the leftward shift in Ghana's firm size distribution. Section 6 concludes.

2. Data

The analysis draws on two primary data sources: (*i*) two waves of Ghana's National Industrial Census (NIC) – spanning nearly two decades in the immediate wake of liberalization, 1987 and 2003 – and (*ii*) longitudinal survey data from a sub-sample of the 1987 NIC firms, tracking them from 1991 to 2002.

2.1. Census data

The remarkable feature of the NIC data is the dramatic fall in average firm size between the two rounds of the census, indicating a steep trend toward smaller scale activity.

The second and third rounds of the census were undertaken by the Ghana Statistics Office (GSO) in 1987 and 2003, respectively, both with the collaboration of the United Nations Industrial Development Organization (UNIDO). Comprehensive coverage and synchronized variable definitions across the two censuses allow for comparisons across years. The NIC incorporates all manufacturing firms in the country, spanning both the formal and informal sector. Household enterprises are excluded, except in cases where public signs clearly advertise the location of a business enterprise within a residential dwelling. The NIC is enumerated at the plant level, thus multi-plant firms are treated as separate observations. As such multi-plant firms are likely to be quite rare in Ghana, particularly in the private sector, I use the terms plant and firm interchangeably throughout. At the time of writing, the available variables which are common across census rounds are extremely limited. They include the establishment name, location (region and town), and 4-digit International Standard Industrial Classification (ISIC) codes, and persons engaged. Persons engaged includes both employees and unpaid apprentices which constitute a significant share of the small-enterprise workforce. Additionally, in 2003 firm age is also available, which is central to reconstructing historical entry rates in section 4.[4]

As seen in Table 1, the firm size distribution in Ghanaian manufacturing shifted significantly downward between 1987 and 2003. Average firm size fell from 19 to 9 employees per establishment, while the proportion of employment in small and microenterprises (fewer than 30 employees) rose from 33% to 52%.

There is strong evidence this change is genuine, rather than being driven by any change in the coverage of the census between rounds. At least three pieces of evidence corroborate the overall pattern of a large reduction in average firms size. First, as can be seen in Table 1, the downward shift in the size distribution occurred across all size categories. Removing firms with fewer than 10 or fewer than 20 employees – where one might speculate coverage has improved – does not alter the picture of declining firm size.

Second, the NIC figures on employment in the manufacturing sector for 1987 and 2003 closely match the equivalent numbers from the population censuses conducted in 1984 and 2000. As seen in Table 2, the NIC reports 157,084 and 243,516 employees in 1987 and 2003, respectively, while the population census records 137,119 and 229,156 wage employees and apprentices in the manufacturing sector in 1984 and 2000, respectively – which rises to 150,708 and 251,866 after adjusting for trend growth in the three year gap between the population census and NIC. This relatively small discrepancy of just 3 to 4% would make it seem highly improbably that there was severe under-counting in the 1987 NIC. Furthermore, the dramatic expansion in apprenticeship labor – 7.1% annual growth compared to 1.8% for the labor force as a whole, in an occupational category usually restricted to small, Ghanaian-owned, informal enterprises, and generally unpaid – is another indication of increasing informality.

Third, the shift in the firm size distribution is also corroborated by another independent data source: the Ghana Living Standards Surveys (GLSS I-IV), a series of large-scale, household socio-economic surveys conducted in 1987/88, 1988/89, 1991/92 and 1998/99. Kingdon, Sandefur and Teal Kingdon, Sandefur, and Teal (2006) present a picture of the evolution of the urban labor market in Ghana by linking these four surveys, tracking the share of the labor force in public versus private sector wage employment, unemployment and self employment. Between GLSS I (1987/88) and GLSS IV (1998/99), the share of the urban labor force in self-employment rose from 50% to

[4] Data from the 1987 NIC is coded according to Revision 2 of the ISIC, while the 2003 NIC uses ISIC Revision 3, as does the survey data presented in the next section. Because there is no precise translation of three- and four-digit ISIC codes between revisions – short of reclassifying individual firms – analysis is restricted to two digit classification, yielding a total of 17 industries.

63%, while private wage employment grew only slightly and the public sector contracted. Thus the broad picture of increasing informality and a trend toward small-scale activity is consistent across all available, nationally representative data sets.

2.2. Survey data

The Ghana Manufacturing Enterprise Survey (GMES) collected data on a sample of firms over a period from 1992 to 2002. The surveys were conducted by a team from the Centre for the Study of African Economies, Oxford, the University of Ghana, Legon, and the Ghana Statistical Office (GSO), Accra. The surveys from 1992 to 1994 were part of the Regional Program on Enterprise Development (RPED) organized by the World Bank, enabling comparison with similar surveys conducted in other Africa countries over the same period.

The original GMES sample of 200 firms was initially drawn from the 1987 NIC, spanning 10 two-digit ISIC sectors and oversampling larger firms with more than 100 employees. The survey includes a full production and input data, firm-specific input and output prices, measures of the human capital of workers and management, questions on access to finance, taxes and the regulatory environment, etc. Firms were surveyed up to seven times (in 1992, '93, '94, '96, '98, 2000 and 2003) with recall data collected for the intervening years. As firms exited they were replaced with new respondents, creating an unbalanced panel covering a total of 312 firms for up to 12 consecutive years, 1991-2002. The mean and median number of observations per firm are 6.98 and 7, respectively.

Large and small firms in the survey data use strikingly different factor intensities, have different propensities to export, pay different prices for both capital and labor, and face different regulatory environments. These systematic differences provide hints about both the causes and consequences of the shift in the firm size distribution shown above.

As seen in Table 3, larger firms pay substantially higher wages for workers with similar characteristics. Median monthly wages range from US$ 24.08 for firms with fewer than five employees up to US$ 125.87 for firms with over 100 workers. While a portion of this difference is undoubtedly attributable to higher skilled labor usage among large firms, previous studies have found that the remaining firm-size wage effect for workers with similar characteristics is still extremely large. Based on earnings equations estimated for the sector by Söderbom & Teal Söderbom and Teal (2004), a firm with 100 employees will pay roughly double the wage of a firm with 10 employees, controlling for workers' observed and time-invariant unobserved skills.

While large firms pay more for labor, there is evidence that they pay significantly less for credit. A simple way to capture these differences without resorting to econometric estimation is to measure the implied return to capital for each firm using data on profits and the capital stock (Bigsten, Collier, Dercon, Fafchamps, Gauthier, Gunning, Isaksson, Oduro, Oostendorp, Pattillo, Söderbom, Teal, and Zeufack, 2003). In a competitive industry the following zero-profit condition

$$\pi_{it} = p_t q_{it} - w_{it} X_{it} - r_{it} K_{it} = 0$$

provides a solution for the firm-specific interest rate,

$$r_{it} = \frac{p_t q_{it} - w_{it} X_{it}}{K_{it}}$$

where p is the product price, q is real output, w is a firm specific vector of input prices, K measures the capital stock and X is a vector of other factor inputs, including labor. Table 3 reports this measure of r for firms in each size class. Applying the zero profit condition to firms in our sample implies that medium firms must pay an effective interest rate of 58% on capital, compared to an astronomical 1,623% for microenterprises.

Finally, a more direct way to assess credit constraints among firms is simply to ask their managers. The bottom of Table 3 reports data from managers' responses to the question "What are your three biggest problems this year?"[5] The responses across large- and small-firm managers conform to a picture of widespread credit constraints in the informal sector. Credit access is listed as a major problem by nearly 70% of microenterprises and only 20% of large firms. Meanwhile, large firms are eight-times more likely to complain of interest rates, implying that credit is available for a sufficient cost. These self-reported measures of credit access are employed in the estimation of firm growth model in section 5, where I deal explicitly with the problems of endogeneity and measurement error that such self-reported data poses.

3. Graphical Analysis: Growth vs. Selection

One of the main stylized facts to emerge from the recent empirical literature on industrial evolution in developed economies is the existence of clear life cycle among firms: entering cohorts are relatively small and in their early years firms either converge fairly quickly to their long-run size or die (Sutton, 1997). The 2003 Census provides data on firm age, which I divide into the following categories: younger than 1 year, 2-4, 5-9, 10-19, 20-29, and 30 years or older. Figure 1 plots nonparametric estimates of the firm size distribution in logs by age category using the cross-section of firms in 2003 Census.[6]

[5] Respondents were not prompted or given a list of options. Enumerators coded the replies into one of twenty-six categories ex post. The data in Table 3 and the variables used in section 5 are dummy variables taking a value of one if a given issue was listed as either the first, second, or third largest problem.

[6] Plots are based on an Epanechnikov kernel density smoother. For comparability, all plots use a bandwidth of 1.

Consistent with the life-cycle pattern, older firms are consistently larger than those in later cohorts.

However, there is an inherent ambiguity in the patterns observed in Figure 1. Using only a cross-section of firms, it is impossible to distinguish the hypothesis that younger firms grow quickly from the alternative hypothesis of selection: small firms die more frequently and thus average size within a cohort increases as it ages.

Cabral and Mata Cabral and Mata (2003) demonstrate a simple graphical method of distinguishing growth from selection in panel data. Their technique is to compare three distinct firm size distributions at two points in time: the period 1 distribution of all firms; the period 2 distribution of firms which survived between rounds; and finally, with the benefit of hindsight, the period 1 distribution of firms which are known to have survived to period 2.

Figure 2 replicates the test suggested by Cabral and Mata using the Ghana Industrial Census data. [7] The curve with the highest peak shows the distribution of all firms in 1987/88. The remaining curves plot the size distribution of firms which survived between periods, in both the initial round (1988S) and sixteen years later (2003). The relative position of these last two curves provides a simple test of the selection hypothesis: did firms which survived grow during the interim, or were they large to begin with?

The results show that the evolution of firm size over the life cycle is driven almost entirely by selection in Ghana. Rather than starting as a representative sample of the population and growing over time, the Ghanaian firms which survived from 1987 to 2003 had negative average growth. The rightward shift in the distribution over time is entirely due to the fact that surviving firms were abnormally large to begin with. [8]

For comparison, I reproduce the analogous figures from Cabral and Mata 2003, p. 1079 in the left panel of figure 2. The distributions are based on data from Portuguese manufacturing firms, which Cabral and Mata argue are fairly representative of developed country data sets in terms of their size distribution and evolution. As in Ghana, older firms are bigger in the Portuguese data. As seen in the figure 2 however, the pattern of growth and selection in this sample is almost precisely the opposite of that observed in Ghana. The figure shows that for Portuguese manufacturing firms, selection (by size)

[7] Unfortunately, firm age is not reported in the 1987 census, so I am unable to identify the 1987 cohort of entrants. Instead, I trace the evolution of the 1987 population of firms over time. An additional difficulty is encountered in matching firms between the two rounds of the census, as no unique identifier is provided. In the end, I were able to match 236 firms by ISIC code, region, and firm name.

[8] It is important to note that the panel of 305 survivors which I identify represents only about 13% of the firms in the 2003 census which claimed to have entered in 1988 or earlier. Comparing these 305 to the larger population of alleged survivors, average firm size is somewhat larger for those I was able to match. However, this will undermine our conclusion in the text only if these 305 firms grew significantly more slowly than the average for the population of survivors. As shown above, there is no evidence of large discrepancies between size classes in within-firm growth rates in Ghana.

plays a very small role in the evolution of the firm size distribution. Cabral and Mata argue that this finding calls for a reevaluation of the central role given to selection in much of the theoretical literature on industrial evolution, notably Jovanovic Jovanovic (1982).

These contrasting findings have enormous implications for how one views the burgeoning SME sector in Ghana. Were the same explosion of entrepreneurial activity taking place in Portugal, there would be reason to believe that the influx of new firms contained the seeds of future large scale industrial development. Such is not the case in Ghana. Existing evidence suggests that small enterprises die early and small. Conversely, big firms don't represent successful microentrepreneurs that have risen through the ranks of smaller firms. Rather, big firms are born big.

4. Distribution Dynamics

I model the evolution in the distribution of firm size from 1987 to 2003, which I denote F_{1987} and F_{2003} respectively, using a first-order, homogenous Markov chain. The central conceit of the Markov framework is that a firm's fate tomorrow (i.e., its size, or continued existence) depends only on its status today, with no further role for history. While this assumption may be questioned in high-frequency data, in transitions over longer time spans – such as the 16 years used here – growth trajectories will likely overwhelm any bias due to serial correlation in the data (Davis, Haltiwanger, and Schuh, 1996).

There are two main objectives to this modelling exercise. First, I use the transition and exit matrices from the Markov model to reconstruct entry rates and thus measure gross job flows at various points in the distribution. Second, by allowing for more general dynamics than in a linear growth model, I can remain agnostic about the shape of the ergodic distribution of firm size. This allows me to test hypotheses such as those put forward by Quah Quah (1997), who finds that the distribution of per capita incomes across countries appears to be converging to a bimodal distribution, or common claims that African firms exhibit a 'missing middle'.

The Markov model contains three basic sets of parameters: (*i*) entry rates of new firms, (*ii*) transition probabilities between size classes for firms that survive from one period to the next, and (*iii*) exit rates. The latter two categories, transition and exit probabilities, can be estimated fairly directly from the data – and as a result have been analyzed quite extensively by previous studies – while entry rates must be inferred somewhat indirectly. This task of inferring entry rates is the main analytical challenge in estimating a Markov model for Ghanaian firms. As I hope to show, however, firm entry patterns are also the most notable and economically significant component of Ghana's recent industrial development.

The census data distinguish nine size categories, allowing me to represent the distribution of firm sizes as a vector of nine discrete densities, which I refer to as F_t. The distribution in year t is linked to the distribution in the following year by a 9×9 matrix of transition probabilities:

$$\begin{aligned} F_{2003} &= M^{16} F_{1987} \\ &= (B + S'D)^{16} F_{1987}, \end{aligned} \tag{1}$$

where subscripts denote the year of observation and superscripts are exponents denoting the powers of a matrix. The second line decomposes the shift in the distribution into a vector of firm entry or "birth" rates B, a matrix of transition probabilities conditional upon survival, S, and a vector of firm exit or "death" rates, D:

$$B = \begin{pmatrix} b_1 & & 0 \\ & \ddots & \\ 0 & & b_9 \end{pmatrix}, S = \begin{pmatrix} s_{11} & \dots & s_{19} \\ \vdots & \ddots & \vdots \\ s_{91} & \dots & s_{99} \end{pmatrix}, D = \begin{pmatrix} 1 - d_1 & & 0 \\ & \ddots & \\ 0 & & 1 - d_9 \end{pmatrix}$$

The parameters b_i and d_i are birth or death rates, respectively, defined as the number of firms entering or exiting a given size class between two periods as a proportion of those observed in initial period. Element s_{ij} of the S matrix denotes the probability that a firm starting in size class i will transition to class j. Because the S matrix maps the distribution of surviving firms from one period to the next, its rows must sum to one. This is not the case with the combined M matrix, however, which will incorporate entry and exit rates.[9]

4.1. Transition matrices

I use the panel of firms in both the NIC and GMES data to estimate the S matrix, or the probability that firm i beginning in size category p ends up in size category q. Using a multinomial logit form, this probability is expressed as a function of nine dummy

[9] It may not be obvious at first glance why the decomposition in line (1) is additive with respect to entry rates and multiplicative with respect to exit rates. Multiplying through the expression element by element yields the following solution for the final density:

$$F_t = \begin{pmatrix} f_{t,1} \\ \vdots \\ f_{t,9} \end{pmatrix} = \begin{pmatrix} b_1 f_{t-1,1} + \sum_{i=1}^{9} s_{i1} d_i f_{t-1,i} \\ \vdots \\ b_9 f_{t-1,9} + \sum_{i=1}^{9} s_{i9} d_i f_{t-1,i} \end{pmatrix}$$

This expression is arguably more intuitive: the number of firms observed in class 1 in period t is equal to the new entrants in that class ($b_1 f_{t-1,1}$) plus the sum of all firms moving into or remaining in class 1. Because transition probabilities are estimated conditional on firm survival, exit rates must be multiplied by the original density before allowing for firm growth.

variables corresponding to each of the firm size classes:

$$s_{pq} = \frac{\exp(\beta_q I(n_{i,t-1} \in p))}{1 + \sum_q \exp(\beta_q I(n_{i,t-1} \in p))} \tag{2}$$

where $I(.)$ is the indicator function, taking a value of one if $n_{i,t-1}$ falls in size class p and zero otherwise. These probabilities, s_{pq}, correspond to the individual elements of the transition matrix, S.[10]

One advantage of the multinomial logit model for this problem is that it imposes the restriction that all probabilities sum to one. The Markov model also suggests additional constraints which can be imposed on the β parameters. It is intuitively clear that the true S matrix should map the original 1987 firm size distribution to the distribution of surviving firms in 2003. However, there is no guarantee that straightforward multimonial logit estimates of S will satisfy this condition. This is because estimation of (2) relies only on data from the sample of 305 firms that can be tracked across both rounds of the census. To put this more formally, let $F^s_{2003,t}$ denote the distribution of firms born in period t and observed in 2003, i.e., the distribution of survivors from the period t cohort. This distribution of survivors should reflect the cumulative transitions and exits occuring since period t, such that

$$F^s_{2003,\leq 1987} = (S'D)^{16} F_{1987}. \tag{3}$$

To improve the fit of the model, it is possible to impose (3) as a constraint on the likelihood maximization used to estimate (2).[11]

Table 6 presents estimates of the 16-year transition matrix based on the NIC, using

[10] Ideally, these probabilities could be estimated for every point on a continuous distribution using, for instance, a stochastic kernel estimator as advocated by Quah Quah (1997). Such an approach avoids the need to impose an arbitrary discretization on the distribution, as this may effect the dynamics of the Markov chain. In the present application, however, the nine discrete size categories used in the analysis were dictated by the available data.

[11] The system of equations in 3 is clearly non-linear with respect to β_q. I rely on a linear approximation of these constraints to enable me to implement them with the `constraint` option on the standard `mlogit` command in STATA. In keeping with the earlier notation, let $f^s_{q,2003,\leq 1987}$ be the q^{th} individual element of the $F^s_{2003,\leq 1987}$ distribution, i.e., the number of firms born in or before 1987 and observed in 2003 in size class q. Then the system of constraints in (3) can be written as:

$$f^s_{q,2003} = \sum_{p=1}^{9} s_{pq} d_p f_{p,1987} \qquad \text{for} \qquad q = 1, 2, \ldots, 9.$$

Substituting 2 into 3 yields

$$f^s_{q,2003} = \sum_{p=1}^{9} \frac{\exp(\beta_q I(n_{i,t-1} \in p))}{1 + \sum_q \exp(\beta_q I(n_{i,t-1} \in p))} d_p f_{p,1987}.$$

The first order Taylor-series approximation of $\exp(\beta_q)$ around $\beta_q = 0$ is simply $1 + \beta_q$. However, I am interested in an approximation to β_q around its true value, which may be far from zero. To circumvent this problem, I assume that the unconstrained estimate of $\tilde{\beta}_q$ is a reasonably close approximation of the

the sample of firms that were tracked between rounds. Starting sizes are listed along the left hand side and ending sizes are listed on the top of the matrix. Blank spaces represent zero probabilitiy events. If the distribution is completely stable, all mass should be found on the diagonal.

There are several notable features about the figures in the table. First, the modest average net growth rates observed in the previous section belie a high level of churning in the firm size distribution and considerable heterogeneity in growth rates. Firms beginning in the middle size ranges fan out to virtually all points in the distribution over 16 years. Second, in the jargon of Markov analysis, the system is said to communicate across the entire distribution. This simply means that all size classes are, in a probabilistic sense, achievable from any given starting point over a sufficiently long span of time (i.e., repeated iterations of the matrix). It is significant to point out, however, that even over the fairly long time span used here, there are no observed cases of microenterprises maturing into large scale employers. Third, the bottom row of the table presents the ergodic distribution implied by the transition matrix. Assuming infinite lives for all firms, there is evidence of an emerging bimodal distribution among Ghanaian firms. While the actual realization of this distribution is prevented by firm death, this pattern is further evidence that small and large firms should be understood as fundamentally different, rather than simply occupying different points in a life-cycle trajectory.

4.2. Exit rates and the selection process

What role did firm exit play in the evolution of the firm size distribution in Ghana from 1987 to 2003? Even if growth and entry rates were identical across size classes, the shift in the firm size distribution over this period may have occurred simply due to accelerated death rates at the upper end of the distribution. The economic reforms of the 1980s may have had a particularly harsh effect on large enterprises (Appiah-Kubi, 2001; Asante, Nixson, and Tsikata, 2000). Liberalization brought the end of many policies – such as subsidized credit schemes, priority access to foreign exchange, and *de jure* product market monopolies – which had previously benefit large firms. Thus, as a simple descriptive statistic, it is informative to compare exit rates across size classes. In addition, these rates are a necessary ingredient in calculating transition and entry rates in the following sections.

---

true parameter. This allows me to write

$$\exp(\beta_q) = \exp(\tilde{\beta}_q)\exp(\beta_q - \tilde{\beta}_q) \approx \exp(\tilde{\beta}_q)(1 + \beta_q - \tilde{\beta}_q),$$

which I use to linearize the system of constraints in (3). Once linearized the constraints can be implemented with standard software packages. Estimation proceeds in two stages. In the first stage estimates of $\tilde{\beta}_q$ are obtained from unconstrained estimation of (2). These estimates are then used to linearize (3) and the multinomial model is re-estimated with the approximated constraints.

I compute firm exit rates, or the parameters of the D matrix, using the GMES sample. The GMES data set is well-suited for measuring exit rates as it contains an indicator variable which distinguishes genuine firm exits from other forms of sample attrition, e.g., manager's refusal to participated in the survey in subsequent rounds, enumerator's inability to locate a micro-entrepreneur who may have relocated his or her business, etc. Such information is not available in the census. Using this variable, I estimate probit model of firm exit where the right hand side variables include dummies for each size class and, in some specifications, controls for location, firm age and year of the survey. The exit probit is estimated over two year intervals, using data from 1991, 1993, 1995, 1997 and 1999.[12] Intermediate rounds are based on recall data and thus, by construction, it is impossible to observe exits in these periods. Size classes are defined in one of two ways: using firm employment in the final survey round prior to employment, or using average employment for all rounds in which data are available. The former measure of firm size may give misleadingly high exit rates for small firms if, as found in other data sets, firms tend to shrink before dying. Measuring size over all available periods mitigates this concern.

Table 5 presents the results of the exit probit, giving a simple descriptive view of firm exit in Ghana's manufacturing sector. The large and highly significant, negative coefficient on firm size in all specifications reflects the simple, unconditional descrptive statistic that annual exit rates for micro firms (less than 10 employees) are roughly ten times higher than for large firms (more than 100 employees), or 5.1% and 0.6% per annum respectively. Columns 2 and 3 show that a significant life-cycle in firm survival is observable only after controlling for ownership variables, and even then is extremely 'shallow', with exit rates varying by only one or two percentage points over the life-cycle. In contrast, state ownership has a strong *positive* effect on firm exit, confirming results in Frazer Frazer (2005). An obvious explanation for this pattern is the divestiture program carried out during the 1990s, in which many poorly performing firms were simply liquidated.[13]

4.3. Entry rates: Rehabilitating the 'myth' that small firms create most jobs

The past decade of research on job creation and destruction in the U.S. has helped to dispel the myth that most jobs are created by small firms. Correcting for the sta-

[12] I also omit the 2002 round of data from the exit model due to the three-year gap after the previous round of data collection – in contrast to the two-year span between all other rounds. Uneven spacing between rounds renders the coefficients on the probit model somewhat difficult to interpret.

[13] Empirical studies on firm exit often highlight the role of TFP in determining firm survival as part of a process of creative destruction (Jovanovic, 1982; Haltiwanger, Scarpetta, and Schweiger, 2006). While TFP measurement is beyond the scope of this paper, two recent published empirical papers have examined the determinants of firm exit in the GMES sample from this theoretical perspective. Results suggest that selection on TFP growth may be present, but is particularly weak among microenterprises Söderbom and Teal (2004); Frazer (2005).

tistical fallacies described in section **??**, the data show the opposite to be true (Davis, Haltiwanger, and Schuh, 1996). Research on firms in Africa – including portions of the GMES data set for Ghana – have reached the same conclusion. Teal Teal (1999) argues that the dominance of small firms in job creation is a myth in Ghana as in the U.S.. Van Biesebroeck (Van Biesebroeck, 2005) compares data from the RPED surveys in nine countries and concludes that large firm growth significantly outpaces the small firm sector.

This section attempts to show that for the case of Ghana, the 'myth' that small firms create most new jobs is in fact reality. The opposite finding by earlier studies has a simple explanation in their common methodology: the analysis of longitudinal surveys based on a sample of firms. The primary defect of most panel data sets for studying job creation is that they systematically ignore new firm entry. Such longitudinal samples thus become increasingly unrepresentative of the population over time, due non-random attrition and the exclusion of new cohorts.

The basic summary statistics from two rounds of the industrial census in Ghana(Table 1) clearly show a dramatic increase in the number of firms in the manufacturing sector as a whole. Furthermore, the bulk of this net increase in the firm population has ended up in the smallest size categories. Formally speaking however, it is not possible to infer entry rates from this table. To do so requires making an allowance for growth and transitions since the time each successive cohort entered. In principle, the increasing mass in the microenterprise sector in Table 1 could reflect a stable pattern of firm entry over the past two decades, with a gradual decline in firm size for existing firms. Alternatively, this shift could reflect a rapid acceleration of firms entering and permanently remaining in the microenterprise sector. In matter of fact, the calculations below show the latter to be closer to the truth.

Firm entry rates for each year, size, region, and industry cell are calculated by combining the estimated transition matrix, $\hat{S}$, with estimated death rates, $\hat{D}$, and information on the *age* distribution of firms in 2003. In addition to the starting and ending distributions, F_{2003} and F_{1987}, the 2003 round of the NIC also provides data on firm age, allowing me to identify survivors from each annual cohort of firms – ranging from one surviving firm born in 1901 to 2,327 surviving firms born in 2002. Denote the cohort of firms born in period t and surviving until period 2003 by $F^S_{2003,t}$. Similarly, with the implicit benefit of hindsight, let $F^S_{t,t}$ equal the cohort of firms born in t, observed in t, and destined to survive until 2003. To clarify, these definitions imply

$$\begin{aligned} F^S_{2003,t} &= (S'D)^{2003-t} F_{t,t} & (4) \\ &= (S')^{2003-t} F^S_{t,t}. & (5) \end{aligned}$$

Again, the first subscript denotes the year a distribution is observed, the second denotes the year its members were born. Distributions without a second subscript refer to the entire population.

Solving equation 5 to recover an estimate of the population and size distribution of an entering cohort of firms, $F^S_{t,t}$, is not straightforward. The first obstacle is finding an appropriate measure of the inverse of the sixteen-year transition matrix, $(S')^{2003-t}$. In an empirical Markov application, the inverse of a matrix as typically defined by linear algebraists will produce potentially nonsensical results in economic terms. For instance, solving equation 5 through simple linear algebra yields a solution implying a *negative* number of firms in several size classes in 1987. This problem is discussed in the appendix. The simple solution, rather than inverting the S matrix, to estimate it in reverse. Second, solving equation 5 requires computation of the sixteenth-root of the S matrix. This can be done both analytically or numerically, and results are presented in the appendix.

With estimates of entering cohort sizes in hand – i.e., estimates of $F^S_{t,t}$ for each year t between 1987 and 2003 – it is possible to examine gross job creation and destruction over time. To do so, I decompose employment changes into four mutually-exclusive and comprehensively exhaustive sources of gross job creation and destruction: job creation in continuing firms, JCC; job creation through firm entry, JCE; job destruction in continuing firms, JDC; and finally job destruction due to firm exit, JDE. Following Davis Davis, Haltiwanger, and Schuh (1996), these statistics are defined as follows:

$$JCC = \sum_{i \in jst} \frac{\Delta^+ e_{ijst}}{\bar{e}_{ijst}} \quad (6)$$

$$JDC = \sum_{i \in jst} \frac{\Delta^- e_{ijst}}{\bar{e}_{ijst}} \quad (7)$$

$$JCE = \bar{e}_{jst} \sum_{i \in jst} I(i = \text{entering firm}) \quad (8)$$

$$JDE = \bar{e}_{jst} \sum_{i \in jst} I(i = \text{exiting firm}) \quad (9)$$

Table 7 presents these statistics for each available size class. The first point to note is the disproportionate contribution of microenterprises in job creation. While it is true that among surviving firms there is no tendency for small firms to grow faster than large firms, there are large disparities in job creation through new firm entry. Looking at the extremes, job creation rates via firm entry for firms with fewer than five employees are over 20% per annum (new jobs in new firms as a share of last period's employment), while the same figure for firms with over 500 employees is just 2.3%. While similar disparities exist in job destruction through firm exit (8.7% for micro firms and effectively 0 for the largest firms), this gap is insufficient to compensate for the massive influx of new small and medium enterprises.

Table 8 attempts to put these figures in international perspective. Recent work by Bartelsman, Haltiwanger and Scarpetta Bartelsman, Haltiwanger, and Scarpetta (2005) and Haltiwanger, Scarpetta and Schweiger Haltiwanger, Scarpetta, and Schweiger (2006) presents comparable data on the firm size distribution, job creation and job destruction in a range of developing and transition countries. However, these papers present no data for African or other low income countries, thus Ghana makes an interesting comparative case study. As seen in the table, while there is no strong tendency for the share of firms or employment in the small-firm sector to vary with per capita GDP, Ghana first in both these categories. Ghana is the only country on the list with less than half its manufacturing workforce in the large firm sector, defined as greater than 50 employees. However, in terms of both gross and net job reallocation rates by size class, the international field shows enormous variance, placing Ghana within a fairly standard range. This includes conforming to a slight tendency for the poorer countries in the list to exhibit faster growth rates in the small and medium enterprise sector during the 1990s relative to the large firm sector.

5. Underlying Determinants of Growth: The Role of Credit Constraints

Why then do the increasingly large, entering cohorts of micro-enterprises documented above fail to move up through the firm size distribution? As noted in Section 2, Table 3, the overwhelming response given by owners and managers of small firms is a lack of access to credit. This is listed as a major obstacle to firm growth by just over 69% of both micro- and small-enterprise owners.

This section attempts to take these concerns seriously, presenting a simple model of the evolution of the firm size distribution in the presence of credit constraints, and drawing on the GMES data to estimate the quantitative significance of this constraint in explaining the observed distribution dynamics.

I begin with the production side of a neoclassical model of firm size (Lucas, 1978).Each individual in the economy is assumed to have some level of managerial talent, θ, which will determine the efficiency of any firm he or she manages, and in turn its optimal size. Production is given by

$$y_{it} = \theta h[f(n_{it}, k_{it})] \tag{10}$$

where $f(.)$ is a standard production function employing capital and labor, couched within a managerial technology, $h(.)$, which is assumed to be concave. Profit maximization based on (10) yields a solution for optimal firm size measured in employment terms:

$$n^*_{ijt}(\theta_{ij}) = \text{argmax}\{\theta_{ij}h[f(n_{ijt}, k_{ijt})] - wn_{ijt} - rk_{ijt}\}. \tag{11}$$

The concavity of the $h(.)$ function ensures that the optimal "span of control" for a manager with a given talent level is well defined even with an underlying constant-returns to scale production function.

In the language of the growth literature, I focus on transition dynamics. For the sake of empirical analysis, I allow that each firm will have an idiosyncratic long-run equilibrium growth rate, g_{ij}, whose determinants are outside the scope of the analysis and will be captured in firm fixed effects.

I introduce credit constraints as an indicator variable, C_ij, denoting the inability to acquire finance at the market interest rate. Credit constraints, as I use the term, imply a market failure. In contrast, firms which are simply priced out of the market for finance by their inability to pay competitive interest rates would not be considered constrained.

Suppose that each entrepreneur is endowed with initial wealth ω, which for simplicity is measured in firm size units (i.e. the maximum number of employees the entrepreneur can afford to hire). This yields a starting firm size of n^*_{ijt} if unconstrained and $n(\omega_{ij})$ if constrained – i.e., the largest size permitted by the initial capital endowment.

In the subsequent period, unconstrained firms will be on their equilibrium growth path, g_{ij}. Firms facing credit constraints, however, will begin the period at an initial size dictated by their wealth endowment, and will be able to grow only insomuch as the business generates profits to finance expansion toward the optimal size n^*_{ij}. Thus firm growth will be a function of credit constraints, past profits, and underlying efficiency

$$\Delta n_{ijt} = \Delta n(\tilde{C}_{ij}(\theta_{ij}), \pi_{ijt}, \theta_{ij}) \tag{12}$$

or more explicitly,

$$\Delta n_{ijt} = \begin{cases} \bar{g}_{ij} & \text{if } C_{ij} = 0 \\ \\ \min(n^*_{ijt}(\theta_{ij}) - n_{ij,t-1}, \pi_{ij,t-1}) & \text{if } C_{ij} = 1 \end{cases} \tag{13}$$

The equations in (13) state that unconstrained firms grow at an exogenous rate, while constrained growth will be the lesser of the gap between current and optimal size, or the expansion feasible with available financing.

The model presents a clear empirical test for the presence of credit constraints: profits should impact growth only for firms which are suspected to be credit constrained.[14] To take the model to the data, as a measure of internal finance I use the log of firm

[14]This result is closely analogous to a central result from the literature on finance and corporate investment. Based on q-theory, investment by publicly traded firms should be independent of internal liquidity after controlling for the stock market value of the firm. The significance of internal liquidity measures in investment equations has been widely interpreted as an indication of capital market inefficiencies (Fazzari, Hubbard, and Petersen, 1988).

profits per employee in the base year. To measure credit constraints, I employ the self-reported data on managers' complaints summarized in section 2. This yields the following empirical analog of equation (13),

$$\begin{aligned} \Delta n_{ijt} &= \beta_0 + \beta_1 \tilde{C}_{ijt} + \beta_2 \ln \pi_{ij,t-1} + \\ &\quad \beta_3 (\tilde{C}_{ijt} \times \ln \pi_{ij,t-1}) + \mathbf{X}_{k,ijt}\beta_k + \upsilon_{ijt} \end{aligned} \tag{14}$$

where i indexes firms, j denotes the industrial sector, $\mathbf{X}$ is a vector of controls and υ_{ijt} is a stochastic error term.

There are two primary econometric challenges in identifying the impact of credit constraints on firm growth in equation (14). The first is measurement error. The survey questionnaire contains a very coarse measure of self-reported credit access. If some genuinely constrained firms fail to mention this in the interview – or vice versa – the estimates of the impact of credit constraints will be biased toward zero.[15]

The second, more conceptual econometric problem stems from the joint determination of credit constraints and firm performance. A rational lender will use all available information to assess the expected profitability and risk profile of a loan application – and by extension, the probability of repayment. This will likely include current and past business performance, including firm growth. Thus any observed negative correlation between credit constraints and firm growth may reflect a causal relationship in either direction.

My empirical strategy to identify the causal effect of credit constraint in the presence of these two sources of bias – measurement error and reverse causation – is to distinguish between putatively exogenous sector specific constraints and firm level idiosyncracies in reporting. This approach is similar to recent work by Fisman and Svensson Fisman and Svensson (2007) who use self-reported bribery data to investigate the impact of corruption on firm performance in Uganda. Decompose the 'raw' credit constraint response – the binary variable $\tilde{C}_{ij}$ – into two components, the sectoral average indexed by j and an idiosyncratic component indexed by i.

$$\tilde{C}_{ij} = C_j + C_{ij} \tag{15}$$

Now consider the two sources of bias discussed above. If the data contain independent, mean zero, measurement error across firms, this error will be restricted to the C_{ij} component. Similarly, for the sources of simultaneity bias, if credit access is driven by specific

[15]It may of course be optimistic to assume that measurement error is random. One might hypothesize that individual firms which are simply inefficient relative to their competitors and unable to *afford* finance, will report credit constraints. The instrumentation strategy employed here will remove the effect of these non-random measurement errors as well, essentially by ignoring any firm-specific idiosyncratic component to the credit constraint measure.

knowledge of an individual firm's efficiency or growth potential, this will again be captured in the C_{ij} term. In contrast, exogenous sources of credit constraints are likely to be constant across firms in a similar sector, size class or region. For instance, if credit is rationed because of legal difficulties in enforcing repayment in the informal sector, or because the fixed costs of lending cannot be justified by the small loans demanded by small firms, these effects will be common across firms in the same sector-size-region cell.

In short, endogenous variation is largely captured in the idiosyncratic firm-level variation in $\tilde{C}_{ij}$, while differences across j cells are putatively exogenous. This suggests that local means of the credit constraint variable will serve as a valid instrument for firms' own reports in equation 14.

A similar problem – and a similar solution – arise in the measurement of profits as well. Cross-sectional and time-series variation in profits may arise for any number of reasons, many of which can be treated as exogenous for the purposes of an employment growth regression. For instance, transitory fluctuations in demand, relative prices, input availability or costs will constitute a shock to profits which should not affect the firm's optimal scale. Other sources of variation in profits are more problematic. Variations in market power between firms, growth in technical efficiency for a given firm relative to its competitors, and so on should produce effects on firm growth independent of credit constraints. Measurement error in firms' profits accounts is of course also a concern.

Once again, I rely on sector averages to instrument firm level profits in equation (14). Decomposing profits in a similar fashion to line (15), the sector specific component of profits, π_j, captures forces that are arguably exogenous to the firm. It is possible to conceive of scenarios which will invalidate this instrument – for instance, a permanent technological shock raising the productivity and optimal scale of all firms in a given sector. It should be noted, however, that there is no reason to expect such a shock to have a disproportionately positive effect on credit constrained firms. Thus finding a positive coefficient on β_3 remains a putatively valid test for the importance of credit constraints.

Estimates of equation 14 show strong support for the model in the previous section. Table 9 presents various specifications of this basic model using the GMES data. The OLS point estimates in column 1 conform to the basic predictions of the model, although the results are insignificant. The insignificant association between the credit constraints indicator and firm growth is perhaps surprising, but fits with the story of endogeneity above. If managers who are particularly eager to expand their firms are those which complain of credit constraints, this may mask the true negative impact of the market failure. Additionally, simple noise in this self-reported measure of constraints will also bias the point estimate toward zero and insignificance.

The left side of Table 9 presents instrumental variables estimates of the growth equation, using as instruments the average values of the credit constraint variable within a firm's sector, size class and region. As with the OLS, the IV point estimates in column 3 conform to the basic predictions of the model. In this case, however, the magnitude of the effects is dramatically increased and significantly different from zero. On their own, log profits still have effectively zero correlation with firm growth. The instrumented credit constraints variable now shows an even larger negative correlation with growth (coefficient of -1.24) and the interaction between credit constraints and log profits is significant and positive. Adding firm fixed effects to the model in column 4 prevents the estimation of the simple credit constraints effect, as this variable does not change over time, but confirms the pattern of interactions with log profits. This pattern of coefficients is consistent with a model in which firms gradually overcome lack of credit access by financing expansion through internal profits.

Finally, it is worth considering how far these these estimated effects can explain the collapse of average firm size and the long run tendency toward a right-skewed firm size distribution identified in section 4. The predicted values from the regressions give some indication that the actual economic importance of these effects may be quite modest. The average predicted values from the growth model in column 3 for firm with fewer than 10 and greater than 100 employees are approximately -3.7% and 1.9%, respectively. I simulate the relaxation of credit constraints by re-calculating predicted growth rates, setting the credit constraint variable (and its interaction with profits) to zero for all firms. The predicted rate for small firms rises from -3.7% to -2.1%, while that for large firms is virtually unchanged at 1.9% and 1.5% with and without constraints, reflecting the near absence of credit constraints in this size class. What is noteworthy is that, while the gap between small and large firms for these 'unconstrained' growth rates is reduced, the difference is not dramatic. Importantly, they suggest that even a major intervention to overcome credit market failures would be insufficient to produce convergence between large and small firms or correct the right skewness in the ergodic firm size distribution.

6. Conclusions

In 1994 the World Bank published a widely cited review of reform efforts in Africa (World Bank, 1994), written partly as a response to critics who argued that Bank-funded structural adjustment programs had entailed social displacement and industrial decline (Stewart, Lall, and Wangwe, 1992). In the discussion of industrial development, the report drew on the first three rounds of the RPED surveys in Ghana to defend the track record of liberalization.

> The picture in Ghana, the country with the most extensive adjustment, is not one of stagnation and deindustrialization; instead, it shows much activity, particularly among smaller enterprises not included in official statistics. (World Bank, 1994, p. 149)

In short, the early RPED studies were already pointing to the boom in microenterprise activity. The report acknowledged, however, that there was not – circa 1994 – sufficient evidence to fully investigate the impact of liberalization on industrial development or job creation.

> The big question is whether the activity of small firms is a structural break with the past or simply a sign of distress. Are many of the smaller new entrants simply household efforts to survive at the margin, or are they dynamic new enterprises that can significantly increase employment in the future? (World Bank, 1994, p. 152)

More than a decade later, data now exist to answer this question. Two clear departures from existing 'stylized facts' in the literature emerged from the analysis of firm entry, growth and exit between 1987 and 2003. First, contrary to previous studies on African data sets which have ignored firm entry (and a wealth of evidence on U.S. data), I find that microenterprises accounted for the bulk of gross and net job creation over the period from 1987 to 2003. Massive new entry of small firms drove average firm size in the sector down by over 50%. Second, contrary to findings from developed country data sets, these entering firms do not appear destined to become medium or large scale enterprises over time. It is selection, rather than within-firm growth, that drives the apparent 'life-cycle of firms' observed in cross-sectional data.

The contrast with results from developed country data sets on this front is extremely telling. Were the same explosion of entrepreneurial activity taking place in Portugal, there would be reason to believe that the influx of new firms contained the seeds of future large scale industrial development. Such is not the case in Ghana. Existing evidence suggests that small enterprises die early and small. Conversely, big firms don't represent successful microentrepreneurs that have risen through the ranks of smaller firms. Rather, big firms are born big.

The final part of the paper examined the potential for improvements in the functioning of credit-markets to promote growth among small and microenterprises. Instrumental variables estimates provide compelling evidence that credit constraints constitute a significant drag on firm growth. Rather than dissipating over time, these constraints have a permanent effect on the firm size distribution and may contribute to significant inefficiencies in resource allocation. However, the importance of credit constraints should not be oversold. My econometric evidence suggests that removing such constraints would be insufficient to overcome the downward slide in the firm size distribution. Further analysis of the role of credit constraints at the point of firm entry may shed additional light on this topic.

From a policy perspective, the Ghanaian experience calls into question the assumed link between market reforms and the decline of the informal sector, or the emergence of a robust large-firm sector. Additionally, policy prescriptions stressing credit market interventions to overcome slow-growth among microenterprises require further justification as credit constraints cannot fully account for the right skewness in the Ghanaian data. From a methodological perspective, the main lesson of this paper is the need to account explicitly for firm entry in the analysis of industrial dynamics. In the design of future data collection efforts, one simple improvement would be to rely on rolling panels that account for changes in the broader distribution of firms, rather than relying exclusively on cross-sections or tracking a fixed sample of firms, as in most existing panel data sets from low-income countries.

Appendix: Further Details on the Calculation of Entry Rates

A. Reversing the Markov Chain

To calculate the distribution of entering firm cohorts it is necessary to solve equation 5 to recover an estimate of $F^{S}_{t,t}$. Simplifying notation for illustrative purposes, I rewrite this equation as

$$F_t = S^t F_0$$

so that the goal is to recover F_0. Solving for F_0 is complicated by the fact that S^t is estimated with error. Due to this measurement error, it is clear that

$$\begin{aligned} F_0 &= S^{-t} F_t \quad \text{and} \\ &= \widehat{S^{-t}} \widehat{F}_t, \quad \text{but} \\ &\neq \widehat{S^{-t}} F_t, \end{aligned} \tag{16}$$

where hats denote empirical estimates, S^{-t} is the matrix inverse of S^t, and S^t is in turn the t^{th} power of the S matrix. Even if the transition matrix is estimated with reasonable precision, $\widehat{S}^t \approx S^t$, the expression in line (16) may fail to provide even a rough approximation to the F_0 distribution. This is because the process of inverting an estimated matrix will magnify the effect of measurement error exponentially.

The solution is to estimate the transition matrix in reverse, which I label S^t_r. This 'reverse matrix' is based on a multinomial logit model, identical to equation 2, but with the dependent and independent variables transposed – i.e., starting size classes are a function of ending size classes. Thus element mn of the S^t_r matrix gives the probability of beginning in size class m conditional on ending up in size class n. Using this calculation I can empirically confirm that $F_0 \approx \widehat{S^t_r} F_t$. Estimates of $\widehat{S^t_r}$ based on the NIC data for the sixteen year span from 2003 to 1987 are presented in the top panel of Table 10.

Mathematically, these two distinct matrices – the algebraic inverse and the 'reverse transition matrix' – represent just two of the infinite possible solutions to the system of equations embodied in 5. Crucially, the reverse matrix is the solution suggested by the data.

B. Using the Markov Chain to Estimate Entering Cohorts

Using the estimates of the sixteen-year reverse transition matrix, it is possible to recreate the implied initial distribution of firms at time zero (in this case, 1987) based on the distribution in time t (2003). While this is empirically uninteresting – as the 1987 distribution is directly observed – it is possible to use the same method to recreate the distribution of firms at other points in time that are not directly observable.

In particular, I am interested in estimating the distribution of entering cohorts – the distribution of firm size in, say, 2002 of firms born in that same period. To do so, I begin with the distribution of firms born in 2002 which survived until 2003. The distribution of these survivors has clearly evolved since entry, both through exit and size class transitions. To recreate their initial distribution, I multiply the ending distribution by the one-year reverse transition matrix and the inverse of the death matrix, as implied by equation 5. To estimate entering cohorts in a give year, t, by this method requires an estimate of the transition probabilities over the time period $2003 - t$. These transition probabilities can be calculated as the roots and powers of the $\widehat{S_r^t}$ matrix.

C. Calculating Roots and Powers of the Markov Chain

Define the square-root of a matrix S, such that $S = S^{1/2}S^{1/2}$. If S is a diagonal matrix, its square root can be formed by taking the square root of each of its individual diagonal entries. The same procedure holds for any square matrix that is diagonalizable.

The $q \times q$ matrix S is diagonalizable if there is a matrix V such that $D = V^{-1}SV$ is a diagonal matrix. If S has q independent eigenvectors, V can be formed by the matrix whose columns are these q eigenvectors. Diagonalization presents an efficient method for calculating the powers, or roots, of a matrix, as

$$S^{1/2} = V^{-1}D^{1/2}V$$

and so on for other powers of S.

In empirical applications, an alternative method to this diagonalization is to rely on a numerical approximation. Let $Y_0 = S$ and $Z_0 = I(q)$, the $q \times q$ identity matrix. Denman and Beavers Denman and Beavers (1976) show that through iteration of the following algorithm,

$$Y_{k+1} = \tfrac{1}{2}(Y_k + Z_k^{-1}), \tag{17}$$

$$Z_{k+1} = \tfrac{1}{2}(Y_k^{-1} + Z_k) \tag{18}$$

Y_k converges quadratically to the square root of S.

The bottom panel of Table 10 reports the sixteenth-root of the reverse transition matrix in the top panel, based on the Denman-Beavers algorithm. As a check, I also calculated the same matrix by diagonalization using a mathematical software package (Maple) and reached an indistinguishable result. The estimates in Table 10 are used as the basis to calculate entering cohorts in section 4 of the main text.

References

Appiah-Kubi, K. (2001): "State-Owned Enterprises and Privatisation in Ghana," *Journal of Modern African Studies*, 39(2), 197–229.

Aryeetey, E., and A. McKay (2007): "Ghana: The Challenge of Translating Sustained Growth into Poverty Reduction," in *Delivering on the Promise of Pro-Poor Growth: Insights and Lessons from Country Experiences*, ed. by L. Cord. New York: Palgrave Macmillan.

Asante, Y., F. Nixson, and K. Tsikata (2000): "The Industrial Sector Policies & Economic Development," in *Economic Reform in Ghana: The Miracle and the Mirage*, ed. by E. Aryeetey, and J. Harrigan. Oxford: James Currey, Ltd.

Bartelsman, E., J. Haltiwanger, and S. Scarpetta (2005): "Measuring and Analyzing Cross-Country Differences in Firm Dynamics," National Bureau of Economic Research.

Beck, T., A. Demirgüç-Kunt, and R. Levine (2003): "Small and Medium Enterprises, Growth, and Poverty: Cross-Country Evidence," World Bank Policy Research Working Paper No. 3178.

Besley, T., and R. Burgess (2004): "Can Labor Regulation Hinder Economic Performance? Evidence from India," *Quarterly Journal of Economics*, 119(1), 91–134.

Bigsten, A., P. Collier, S. Dercon, M. Fafchamps, B. Gauthier, J. Gunning, A. Isaksson, A. Oduro, R. Oostendorp, C. Pattillo, M. Söderbom, F. Teal, and A. Zeufack (2003): "Credit Constraints in Manufacturing Enterprises in Africa," *Journal of African Economies*, 12(1), 104–25.

Botero, J. C., S. Djankov, R. La Porta, F. Lopez de Silanes, and A. Shleifer (2004): "The Regulation of Labor," *Quarterly Journal of Economics*, 119(4), 1339–82.

Cabral, L. M. B., and J. Mata (2003): "On the Evolution of the Firm Size Distribution: Facts and Theory," *American Economic Review*, 93(4), 1075–90.

Davis, S., J. Haltiwanger, and S. Schuh (1996): *Job Creation and Destruction.* MIT Press, Boston.

de Soto, H. (1989): *The Other Path*. New York: Harper and Row.

Denman, E., and A. Beavers (1976): "The matrix sign function and computations in systems," *Applied Mathematics and Computation*, 2, 63–94.

Fafchamps, M. (2000): "Ethnicity and Credit in African Manufacturing," *Journal of Development Economics*, 61, 205–35.

Fazzari, S. M., R. G. Hubbard, and B. C. Petersen (1988): "Financing Constraints and Corporate Investment," *Brookings Papers on Economic Activity*, 0(1), 141–95.

Fisman, R., and J. Svensson (2007): "Are corruption and taxation really harmful to growth? Firm level evidence," *Journal of Development Economics*, 83, 63 – 75.

Frazer, G. (2005): "Which Firms Die? A Look at Manufacturing Firm Exit in Ghana," *Economic Development and Cultural Change*.

Ghana Statistical Service (1984): "Report on the 1984 Population and Housing Census," Statistical Service, P.O. Box 1098, Accra, Ghana.

——— (1989a): "Ghana Directory of Industrial Establishments, 1988," Statistical Service, P.O. Box 1098, Accra, Ghana.

——— (1989b): "Ghana National Industrial Census, 1987: Phase 1 Report, Background and Results," Statistical Service, P.O. Box 1098, Accra, Ghana.

——— (2000): "Demographic, Health and Economic Characteristics: Report on the 2000 Population and Housing Census," Statistical Service, P.O. Box 1098, Accra, Ghana.

Grayson, L. (1973): "A Conglomerate in Africa: Public-Sector Manufacturing Enterprises in Ghana, 1962-1971," *African Studies Review*, 16(3), 315–345.

Haltiwanger, J., S. Scarpetta, and H. Schweiger (2006): "Assessing Job Flows across Countries: The Role of Industry, Firm Size, and Regulations," World Bank Policy Research Working Paper No. 4070.

Herbst, J. (1993): *The Politics of Reform in Ghana, 1982-1991.* University of California Press, Berkeley and Los Angeles.

Hopenhayn, H. A. (1992): "Entry, Exit, and Firm Dynamics in Long Run Equilibrium," *Econometrica*, 60(5), 1127–50.

Jebuni, C. D., A. D. Oduro, and K. A. Tutu (1994): "Trade and Payments Regime and the Balance of Payments in Ghana," *World Development*, 22(8).

Jovanovic, B. (1982): "Selection and the Evolution of Industry," *Econometrica*, 50(3), 649–70.

Killick, T. (1978): *Development Economics in Action: A Study of Economic Policies in Ghana*. Heinemann, London.

Kingdon, G., J. Sandefur, and F. Teal (2006): "Labour Market Flexibility, Wages and Incomes in Sub-Saharan Africa in the 1990s," *African Development Review*, 18(3).

Kumar, K., R. Rajan, and L. Zingales (1999): "What Determines Firm Size?," Centre for Economic Policy Research (CEPR) Discussion Paper No. 2211.

Lall, S. (1995): "Structural Adjustment and African Industry," *World Development*, 23(12), 2019–2031.

Lucas, R. E. (1978): "On the Size Distribution of Business Firms," *Bell Journal of Economics*, 9(2), 508–23.

Quah, D. T. (1997): "Empirics for Growth and Distribution: Stratification, Polarization, and Convergence Clubs," *Journal of Economic Growth*, 2(1), 27–59.

Rauch, J. E. (1991): "Modelling the Informal Sector Formally," *Journal of Development Economics*, 35(1), 33–47.

Shiferaw, A., and A. S. Bedi (2009): "The Dynamics of Job Creation and Job Destruction: Is Sub-Saharan Africa Different?," IZA Discussion Papers 4623, Institute for the Study of Labor (IZA).

Söderbom, M., and F. Teal (2004): "Size and Efficiency in African Manufacturing Firms: Evidence from Firm-Level Panel Data," *Journal of Development Economics*, 73(1), 369–94.

Söderbom, M., F. Teal, and A. Wambugu (2005): "Unobserved Heterogeneity and the Relation between Earnings and Firm Size: Evidence from Two Developing Countries," *Economics Letters*, 87(2), 153–59.

Stewart, F., S. Lall, and S. Wangwe (1992): "Structural Problems of African Industry," in *Alternative Development Strategies in Sub-Saharan Africa*. Macmillan, London.

Sutton, J. (1997): "Gibrat's Legacy," *Journal of Economic Literature*, 35(1), 40–59.

Teal, F. (1999): "The Ghanaian Manufacturing Sector 1991-95: Firm Growth, Productivity and Convergence," *Journal of Development Studies*, 36(1), 109–127.

Tignor, R. L. (2006): *W. Arthur Lewis and the Birth of Development Economics*. Princeton University Press, Princeton, NJ.

Van Biesebroeck, J. (2005): "Firm Size Matters: Growth and Productivity Growth in African Manufacturing," *Economic Development and Cultural Change*, 53(3), 545–83.

World Bank (1994): *Adjustment in Africa: Reforms, Results, and the Road Ahead.* Oxford University Press, New York, NY.

Table 1: Census Data on Manufacturing Firms

	1987				2003			
Size	Firms	%	Emp.	%	Firms	%	Emp.	%
1-4	2,884	35	7,400	5	14,352	55	35,834	15
5-9	3,391	41	21,264	14	7,829	30	48,982	20
10-19	1,101	13	14,306	9	2,427	9	30,784	13
20-29	310	4	7,235	5	541	2	12,405	5
30-49	232	3	8,594	5	401	2	14,538	6
50-99	191	2	13,116	8	287	1	18,270	8
100-199	114	1	15,866	10	124	0	16,819	7
200-499	74	1	22,596	14	87	0	26,240	11
500+	52	1	46,707	30	40	0	39,644	16
Total	8,351	100	157,084	100	26,088	100	243,516	100
Ave. Size	19				9			

Source: Ghana Statistical Service, *National Industrial Census 1987, Phase I Report*, and *2005 National Industrial Census Bulletin No. 1.*

Note: Size categories and average size refer to employees per establishment.

Table 2: Manufacturing Employment in the Population Census

	1984		2000		Growth
	Empl.	Share	Empl.	Share	Rate
Wage Employees					
Public	27,172	4.6	34,275	4.3	1.5
Private	65,931	11.2	100,174	12.7	2.6
Apprentices	25,332	4.3	78,834	10.0	7.1
Other	18,684	3.2	15,873	2.0	-1.0
Total Employed	137,119	23.3	229,156	29.1	3.2
Self-Employed					
Without Employees	430,029	73.1	490,276	62.2	0.8
With Employees	21,270	3.6	68,636	8.7	7.3
Total Self-Employed	451,299	76.7	558,912	70.9	1.3
Total	588,418	100.0	788,068	100.0	1.8

Source: Author's calculations based on published statistics from the Ghana Statistical Service census reports 1984; 2000.

Table 3: Firm Characteristics by Size Class

	Micro	Small	Medium	Large
No. Firms	72	77	73	58
No. Observations	854	924	846	676
Average Values:				
Capital Labor Ratio (US$)	1,707.82	3,479.70	8,303.99	17,482.65
Implied Cost of Capital (% p.a.)	16.23	4.24	1.10	.58
Ave. Wage/Month (US$)	24.08	33.35	75.35	125.87
Ave. Yrs. Schooling	9.34	9.47	10.34	11.17
Exports (% Output)	1.87	3.80	6.89	26.77
Imported Inputs (% Total)	9.77	18.80	34.00	33.14
Percentage of Firms:				
Unionized	.00	12.99	55.22	94.44
State Owned	.00	3.90	9.93	8.88
Foreign Owned	4.22	12.99	27.19	46.45
Percentage of Managers Citing:				
Access to Credit	69.49	69.63	44.80	19.83
Interest Rates	3.39	7.41	13.60	25.00
Foreign Exchange	18.64	16.30	32.00	25.00
Import Competition	3.39	4.44	8.80	6.90

Size classes are based on the average size of the firm over all available years, and are defined as follows: micro, 1-9; small, 10-29; medium, 30-99; large, $\geq$ 100.

Table 4: Firm Growth by Firm Size, GMES Sample

	Categorized by Initial Empl.			Categorized by 'Current' Empl.		
	1-yr	4-yr	8-yr	1-yr	4-yr	8-yr
	(1)	(2)	(3)	(4)	(5)	(6)
Size Class 1 to 4	.472	.148	.087	-.002		
	(.133)***	(.046)***	(.030)***	(.023)		
Size Class 5 to 9	.104	.033	.032	-.011	-.004	
	(.032)***	(.018)*	(.022)	(.016)	(.009)	
Size Class 10 to 19	.025	.041	.027	-.004	.0004	.0009
	(.021)	(.027)	(.018)	(.012)	(.004)	(.004)
Size Class 20 to 29	.033	.017	-.003	-.040	-.008	.001
	(.031)	(.021)	(.010)	(.024)*	(.004)*	(.003)
Size Class 30 to 49	.006	-.005	-.016	-.002	-.005	-.005
	(.017)	(.015)	(.012)	(.017)	(.003)	(.002)**
Size Class 50 to 99	-.005	-.023	-.024	-.009	-.005	-.002
	(.019)	(.014)*	(.017)	(.017)	(.003)	(.002)
Size Class 100 to 199	-.002	-.020	-.012	.001	-.006	-.002
	(.021)	(.015)	(.015)	(.015)	(.003)*	(.002)
Size Class 200 to 499	.011	.007	-.006	.008	-.004	-.002
	(.020)	(.016)	(.015)	(.018)	(.004)	(.001)
Size Class $>$ 500	-.061	-.043	-.026	-.035	-.002	-.001
	(.036)*	(.023)*	(.014)*	(.041)	(.002)	(.001)
Obs.	1778	1069	407	1778	1069	407
R^2	.057	.054	.09	.002	.023	.05

The dependent variable is the net growth of employment within the firm over the time span indicated in the first row. Regressors consist of a set of dummies for each size class. In columns 1 to 3, size classes are defined on the basis of initial employment and thus subject to the 'regression fallacy'. In columns 4 to 6 size classes are defined on the basis of 'current' employment, following the definition proposed by Davis, et al. 1996.

Table 5: Firm Exit Probits, GMES Sample

	(1)	(2)	(3)
Ln Empl	-.171	-.165	-.231
	(.057)***	(.059)***	(.086)***
Firm Age		-.018	-.041
		(.017)	(.018)**
Firm Age Sq.		.0004	.0007
		(.0003)	(.0003)**
State Ownership			1.089
			(.461)**
Foreign Ownership			.260
			(.287)
Sector Dummies			Yes
City Dummies			Yes
Time Dummies			Yes
Obs.	500	500	500
R^2	.025	.030	.115

All independent variables are measured at time t, except for employment which is measured by the average of period t and $t-1$ values to adjust for possible employment shedding before exit. The dependent variable is an indicator for firm exit between period t and $t+2$, i.e., the next biannual survey round. The dependent variable measures genuine firm deaths and does not include other forms of sample attrition.

Table 6: Multinomial Logit Estimates of the 16-Year Transition Matrix, NIC Sample

	1 to 4	5 to 9	10 to 19	20 to 29	30 to 49	50 to 99	100 to 199	200 to 499	500+
1 to 4	.688	.313							
	(.067)	(.067)							
5 to 9	.355	.398	.140	.086	.011	.011			
	(.050)	(.051)	(.036)	(.029)	(.011)	(.011)			
10 to 19	.167	.296	.185	.148	.130	.056	.019		
	(.051)	(.062)	(.053)	(.048)	(.046)	(.031)	(.018)		
20 to 29	.067	.133	.400	.133	.200			.067	
	(.064)	(.088)	(.126)	(.088)	(.103)			(.064)	
30 to 49	.050		.150	.100	.350	.150	.100	.100	
	(.049)		(.080)	(.067)	(.107)	(.080)	(.067)	(.067)	
50 to 99			.125	.083	.208	.417		.125	.042
			(.068)	(.056)	(.083)	(.101)		(.068)	(.041)
100 to 199	.040		.080	.120	.120	.200	.080	.280	.080
	(.039)		(.054)	(.065)	(.065)	(.080)	(.054)	(.090)	(.054)
200 to 399						.053	.211	.474	.263
						(.051)	(.094)	(.115)	(.101)
500 +								.571	.429
								(.187)	(.187)
Ergodic	.322	.221	.086	.053	.059	.050	.034	.114	.061

The left column lists starting sizes and the top row lists ending sizes. Entries in the table represent row probabilities, i.e., the probability that a firm starting in a given row will end in a given column. All rows sum to one. Standard errors are listed in parentheses.

Table 7: Gross Job Creation & Destruction Rates by Size Class

	Annual Rates				Shares of Total			
	Job Creation		Job Destruction		Job Creation		Job Destruction	
	Continuing Firms	Entering Firms	Continuing Firms	Exiting Firms	Continuing Firms	Entering Firms	Continuing Firms	Exiting Firms
Size Class 1 to 4	7.0	20.4	8.1	8.7	4.4	12.7	7.9	8.5
Size Class 5 to 9	6.3	12.1	7.5	7.1	3.9	7.5	7.4	6.9
Size Class 10 to 19	7.4	13.4	7.3	6.1	4.6	8.4	7.2	6.0
Size Class 20 to 29	5.8	15.7	7.3	8.2	3.6	9.8	7.1	8.1
Size Class 30 to 49	6.4	14.6	6.7	4.6	4.0	9.1	6.6	4.5
Size Class 50 to 99	7.9	13.6	7.1	5.5	4.9	8.5	6.9	5.4
Size Class 100 t 199	5.3	7.2	5.3	1.2	3.3	4.5	5.2	1.2
Size Class 200 t 499	5.3	4.5	4.1	1.7	3.3	2.8	4.0	1.7
Size Class $\geq$ 500	4.9	2.3	5.6	0.0	3.1	1.4	5.4	0.0
Total					35.1	64.7	57.7	42.3
					100		100	

Table 8: International Comparison: Job Creation & Destruction Rates by Firm Size Class

	% of Firms			% of Emp.			Gross Job Reallocation Rate			Net Job Creation Rate		
	S	M	L	S	M	L	S	M	L	S	M	L
USA	72.6	15.1	12.3	6.7	6.8	86.5	38.6	27.3	13.2	-3.3	1.1	0.5
Germany	83.3	9.0	7.7	16.6	10.7	72.7	26.2	15.7	8.5	-5.5	-0.9	0.0
France	77.9	13.9	8.2	19.9	16.0	64.1	36.1	27.5	25.5	-5.0	-3.8	1.4
Italy	88.6	7.6	3.8	31.1	15.8	53.1	29.8	19.5	17.1	0.3	2.1	0.7
Finland	85.4	7.9	6.7	13.5	8.9	77.6	36.4	25.4	22.0	0.7	-1.3	0.3
UK	81.3	9.6	9.1	12.4	10.0	77.6	37.7	27.4	21.3	1.1	-0.7	-1.3
Portugal	75.3	14.6	10.1	18.9	17.4	63.7	32.7	21.8	15.4	2.1	0.4	-1.0
Argentina	82.1	10.7	7.2	21.3	15.0	63.7	30.4	21.2	15.3	-4.1	-0.7	-1.3
Hungary	71.1	14.0	14.9	8.8	9.2	82	43.1	31.4	20.8	4.6	5.8	0.9
Estonia	64.6	19.6	15.8	11.5	15.0	73.5	40.6	23.6	16.7	6.9	3.0	0.6
Mexico	82.8	8.8	8.4	13.9	9.9	76.2	50.0	33.6	21.7	-4.3	3.1	6.7
Latvia	87.8	7.3	4.9	26.9	14.7	58.4	44.9	29.7	19.8	12.1	6.6	3.0
Brazil	82.4	10.3	7.3	17.7	12.3	70	48.0	34.5	23.2	4.4	7.7	1.8
Slovenia	71.6	8.3	20.1	5.1	4.4	90.5	36.5	30.1	17.0	6.5	0.9	-4.4
Ghana	93.7	3.8	2.5	41.2	9.8	48.9	41.2	37.1	27.0	4.5	6.0	1.9

Countries are listed in descending order of real per capita GDP. Small (S) = less than 20 employees; Medium (M) = 20 to 49; Large (L) = 50 or more. Statistics refer to job creation and destruction rates – the number of jobs created/destroyed as a share of the initial level in a given category, as defined in the text.

Source: Ghana statistics based on author's calculations combining NIC and GMES data. For international comparisons, job creation and destruction rates due to changes in continuing firms and entry/exit of firms are taken from Haltiwanger, Scarpetta and Schweiger 2006, Figure 1, p. 9. Shares of total, national, manufacturing job creation and destruction by size class for each country are taken from Haltiwanger, Scarpetta and Schweiger 2006, Table 5, p. 15. Employment shares by firm size class for each country are taken from Bartelsman, Haltiwanger and Scarpetta 2005, Table 3, p. 20. Job creation rates are constructed using these three published statistics, where $JC\text{Rate}_{sc} = JC\text{Rate}_c * JC\text{Share}_{sc}/\text{Emp Share}_{sc}$.

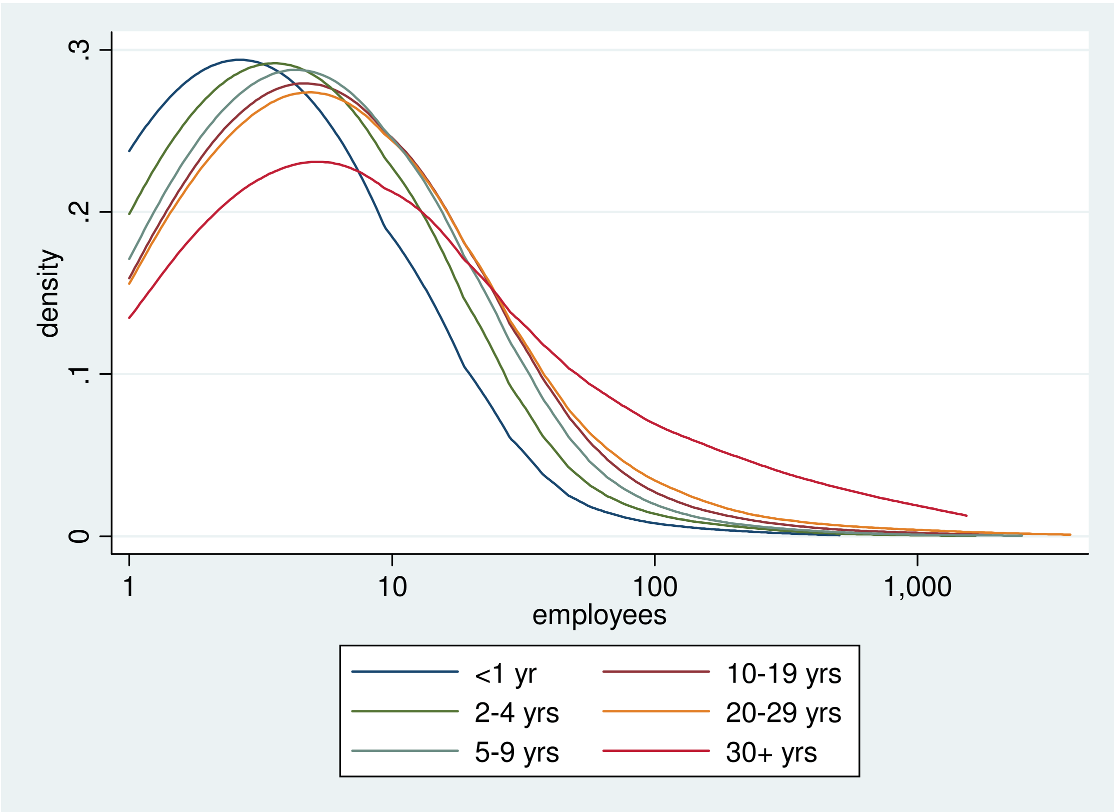

Figure 1: The 'life cycle of firms' from a cross-sectional perspective. (Size distribution of the 2003 population of firms by age category.)

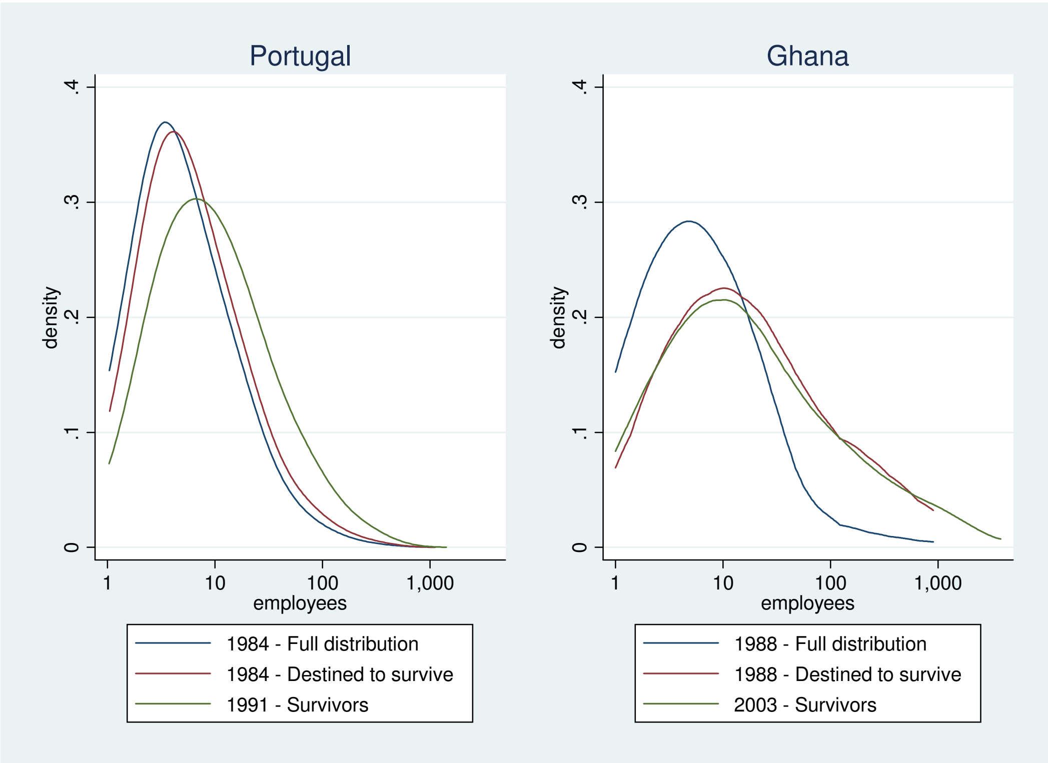

Figure 2: Opposing patterns of firm growth and selection.

Table 9: Credit Constraints & Firm Growth, GMES Sample

	OLS		IV	
	(1)	(2)	(3)	(4)
Log Profit	.009	.055	-.028	.033
	(.007)	(.012)***	(.018)	(.030)
Log Profit × Credit Const.	.019	.0007	.093	.088
	(.014)	(.017)	(.046)**	(.047)*
Credit Const.	-.289		-1.244	
	(.180)		(.606)**	
Firm FE		Yes		Yes
Obs.	1385	1385	1385	1385
R^2	.026	.043	.021	.020

The dependent variable is the first-difference of log employment in the firm. In addition to the regressors listed, all equations include controls for firm age and a time trend. Equations without firm fixed effects also include a full set of indicator variables for firm size classes (based on the average level of employment as described in the text), sectors and regions. The instruments in columns 3 and 4 are the average value within a firm's size class, sector and region for each of the variables listed.

Table 10: Appendix: Multinomial Logit Estimates of the Reverse Transition Matrix, NIC Sample

16-Years	1 to 4	5 to 9	10 to 19	20 to 29	30 to 49	50 to 99	100 to 199	200 to 499	500+
1 to 4	.366	.465	.127	.014	.014		.014		
5 to 9	.214	.529	.229	.029					
10 to 19	.159	.295	.227	0.136	.068	.068	.045		
20 to 29		.320	.320	.080	.080	.080	.120		
30 to 49		.038	.269	.115	.269	.192	.115		
50 to 99		.043	.130		.130	.435	.217	.043	
100 to 199			.111		.222		.222	.444	
200 to 399				0.038	.077	.115	.269	.346	.154
500 +						.091	.182	.455	.273

1-Year	1 to 4	5 to 9	10 to 19	20 to 29	30 to 49	50 to 99	100 to 199	200 to 499	500+
1 to 4	.917	.083	-.005	-.002	.006	-.002	-.001	.009	-.005
5 to 9	.033	.926	.047	.005	-.009	.002	.008	-.022	.011
10 to 19	.017	.052	.885	.015	.025	-.002	-.025	.060	-.027
20 to 29	.001	.038	.016	.914	-.006	.030	.065	-.098	.040
30 to 49	.000	-.032	.061	.036	.898	.034	.018	-.025	.010
50 to 99	.017	-.015	-.015	.030	.007	.951	.045	-.032	.011
100 to 199	-.056	.054	.093	-.107	.054	-.022	.890	.125	-.031
200 to 399	.037	-.031	-.067	.068	.004	.018	.042	.888	.041
500 +	-.023	.015	.043	-.035	-.021	.012	.017	.092	.899

The left column lists *ending* sizes and the top row lists *starting* sizes. Entries in the table represent row probabilities, i.e., the probability that a firm ending in a given row began in a given column. All rows sum to one. Estimates are based on a multinomial logit model of transitions over 16 years. The bottom panel represents the 16^{th} root of the matrix in the top panel, calculated by the Denman-Beavers 1976 algorithm.