Explaining the Trend toward Informal Employment in Africa: Evidence from Ghanaian Manufacturing

Justin Sandefur*
Centre for the Study of African Economies, Oxford University

Preliminary Draft
March 31, 2006

Abstract

During the 1990s the proportion of the urban labor force working in the small scale, informal sector grew dramatically across Africa. We investigate the causes of this trend toward informality by studying the case of the manufacturing sector in Ghana, where the share of workers employed in small and micro enterprizes grew from roughly one third in 1987 to over half in 2003. By combining two waves of an industrial census with a rich panel data set on a sample of firms, we quantify the patterns of firm entry, exit and growth which have produced this trend. We document a significantly different pattern of job creation and destruction than previously found in developed country data sets.

*Special thanks are due to Moses Awoonor-Williams for assistance in obtaining the Ghana Industrial Census data, and to my supervisor, Francis Teal, for consistent guidance and input. The survey data used in this paper were collected by a team from the CSAE, Oxford, the University of Ghana, Legon, and the Ghana Statistical Service (GSS), Accra, over a period from 1992 to 2002. The surveys from 1992 to 1994 were part of the Regional Program on Enterprize Development (RPED) organized by the World Bank. The surveys have been funded by the Department for International Development of the UK Government and the CSAE is funded by the Economic and Social Research Council of the UK.

Contents

1 Introduction

Evidence from across countries (Botero, Djankov, La Porta, Lopez de Silanes, and Shleifer 2004) and across Indian states (Besley and Burgess 2004) shows that the share of informal employment is closely associated with low levels of development and high levels of market regulation. In both the cross-section and time-series dimensions the share of employment in the informal sector declines steadily with per capita income. Controlling for the level of GDP, informality is frequently found to be a result of government interventions which make it costly for firms to grow beyond some threshold size.

With these patterns in mind, Africa presents something of a paradox. During the 1990s, all of the economies discussed below (Ghana, Uganda, Kenya and Tanzania) posted slow but positive growth in per capita GDP. Furthermore, all of these economies undertook substantial (albeit quite varied) market-oriented reforms in the 1980s and early 1990s. Nevertheless, as documented below, all of these economies saw substantial increases in the relative size of their informal sectors.

This paper uses data from the manufacturing sector in Ghana to study features and determinants of this trend in detail. From 1987 to 2003 manufacturing firms in Ghana averaged zero employment growth. However, employment in Ghana's manufacturing *sector* increased by roughly 55% over the same period. These contrasting trends were compatible due to the massive entry of new firms into the sector. However, entering cohorts were dominated by microenterprizes, driving average firm size down by half over the course of 16 years.

Throughout the paper we treat the scale of production as the defining feature of the informal sector. This can be seen in the large wage differentials between large and small firms, of which self-employment is the limiting case. Our analytical framework is taken from the literature on industrial evolution and the determinants of the firm size distribution. In this respect, we build on important work relating labor market segmentation to the firm size distribution in developing economies including Rauch (1991) and Besley and Burgess (2004).

The remainder of this section documents the trend toward informality in Africa and highlights potential causes and consequences of this trend by reviewing previous research. Section 2 an analytical framework focused on efficiency-based selection of firms and the financing constraints facing small employers. Section 4 decomposes the shift in the firm size distribution into entry rates, exit rates, and transitions between size classes using two waves of the Ghana Industrial Census. The results of this decomposition show that rapid entry of new informal firms explains the bulk of this shift. In Section 5 we contrast the relative magnitudes of within-firm growth and new firm entry by comparing our data from Ghana with recent findings from the OECD. Given the importance we attribute to new microenterprize entry in the census data, Section 6 investigates the underlying determinants of firm starting size using more detailed data on a sample of firms. Section **??** concludes.

1.1 The trend toward informality

This subsection presents two perspectives on the trend toward informality in African labor markets. These can be seen as corroborating pieces of evidence documenting the trend which motivates this paper.

First, labor force data from across the region shows a sharp increase in level of self-employment as a proportion of the non-agricultural labor force. Figure 1 summarizes a wide range of data from individual household and labor force surveys to provide an overview of the distribution of employment across sectors at two points in time for five African economies: Ghana, Tanzania, Uganda, Ethiopia, and South Africa.[1] We distinguish between public and private sector wage employment, unemployment and self employment. Because legal definitions of informality vary across countries (and due to data availability), the self employment category provides our best, comparable measure of informality in these economies.

In all five countries the level of wage employment has increased in absolute terms, but failed to keep pace with a growing labor force. However, there has been some divergence between countries in where the resulting excess labor supply has ended up. In South Africa and urban Ethiopia workers unable to find wage employment have swelled the ranks of the unemployed, producing some of the highest unemployment rates in the world (Krishnan (1996) and Kingdon and Knight (2004) provide detailed discussion of these trends). In Ghana, Tanzania and Uganda, however, excess labor has been absorbed into the informal sector in the form of self employment. In these three countries, self-employment has grown not only in absolute terms, but also increased quite rapidly as a proportion of the non-agricultural labor force. For Ghana, this increase was from 50% in 1988 to 63% in 1999. While directly comparable figures are not available, Calves & Schoumaker (2004) report a similar increasing trend toward informality in Burkina Faso while Atieno (2005) reports that the informal share of Kenya's labor force rose from 16% in 1980 to 70% in 2000.

Our second source of evidence for the recent trend toward informality in Africa comes from the perspective of firms. Here we focus on Ghana, for which comparable data from two rounds of an industrial census allow us to examine the evolution of formal and informal employment over time. 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 microenterprizes (fewer than 30 employees) rose from 33% to 52%. As can be seen in Figure 2, this downward shift in the size distribution occurred across all size categories (i.e., cannot be attributed to improved coverage in the smallest size category between the 1987 and 2003 censuses, for instance). Furthermore, while we have suppressed the additional tables to conserve space, the data show that this downward shift in firm size is not due to reallocation of production across industries. Firm sizes fall *within* each of the major 3-digit ISIC industrial classifications in Ghanaian manufacturing.

As with the labor force data, we opt not to impose any single definition of

[1]Details of the data sources underlying Figure 1 can be found in Kingdon, Sandefur and Teal (**?**).

formality or informality on the firm data, such as a specific legal characteristic or threshold firm size. Again, there are multiple reasons for this decision. The most pressing is data availability, as the census provides information only on firm location, industrial classification, age, and the number of employees. Additionally, the regulatory environment in Ghana suggests no clear demarcation between the two sectors - *de jure* regulation appears to be less relevant to most firms than the *de facto* differences in operating costs which increase (or, in the case of capital markets, decrease) proportionally with firm size (Mazumdar 2002).

1.2 Informality & Factor Markets

Large and small firms in Ghana use 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 documented above. In terms of causes, the much higher proportion of imported inputs among large firms suggests that real depreciation of the cedi will have had a differential impact on firms of different size. In terms of consequences, the shift in the average size of manufacturing firms may have significant implications for the sector's export potential and the wages of workers in the industry.

The data used in this section and in the econometric analysis which follows are taken from a survey of Ghanaian manufacturing firms conducted over the period 1991-2002, yielding a panel with up to 12 observations per firm. A total of 312 firms are observed for at least one period, though the panel is unbalanced due primarily to firm exit and replacement in the sample. Summary statistics for the main variables used in the analysis are presented in table 2. As comparison with the census data in table 1 reveals, the sample contains a disproportionately high number of large firms – an imbalance which increases over the sample period. However, given that we do not attempt to measure or explain any aggregate trends in the sample, we view this as a strength rather than a weakness of our data set in that it provides us with information on firms across the size distribution, rather than a more numerically representative sample which would be almost exclusively limited to the smallest firms. Two important contrasts between large and small firms which emerge from the data (and from the wealth of empirical work published on it) are discussed below.

1. *Larger firms pay substantially higher wages for workers with similar characteristics.*

Table 2 points to several direct implications of low firm growth and a shift toward smaller firm sizes. First, large firms pay substantially higher wages, with a median monthly wage rate ranging from US$ 22.60 for firms with fewer than five employees up to US$ 109.92 for firms with over 100 workers. While a significant portion of this difference is attributable to higher skilled labor usage among large firms, 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 (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.

2. *Small firms face extremely high interest rates and are frequently unable to obtain credit at market rates.*

While large firms pay more for labor, there is evidence that they pay significantly less for credit. Bigsten, et al. (2003) investigate the incidence of credit constraints among manufacturing firms in nine Africa countries. They find that firm size is a major determinant of credit access (which may relate to the fixed costs of monitoring loans to small firms, greater collateral among large firms, or simple bias). Predicted profitability is a major determinant of credit access for all firms, but the level of profitability required to receive a loan is much more stringent for small firms. Holding other characteristics constant, on average a medium sized firm will require 56% profitability to have a 20% chance of securing a loan, while a small firm must be expected to earn 200% profits to have an equal chance of gaining credit.

A simple way to capture the differences in credit access which Bigsten et al. document without having to rely on econometric estimation is to measure the implied return to capital for each firm using data on profits and the capital stock. In a competitive industry the following zero-profit condition

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

provides a solution for the firm-specific interest rate,

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

where p is the product price, q is real output, w is a firm specific wage, K measures the capital stock and L is labor. Table 2 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 80% on capital, compared to 1,780% for microenterprizes. Rather than taking the latter number too seriously, this should be interpreted as showing that micro firms are effectively locked out of credit markets, making any measure of the cost of capital fairly meaningless.

Unsurprisingly given these factor price differences, large and small firms also exhibit a wide gap in relative factor ratios. Large firms are nearly ten-times more capital intensive than micro firms, which largely explains the three-fold difference in labor productivity.

To summarize, large firms pay high wages and (relatively) low interest rates, while small firms pay low wages, but are constrained by a lack of capital. Taken together, these complementary stylized facts highlight the potential adverse consequences of the falling firm size distribution for labor market outcomes, as well as some potential constraints which have contributed to this trend.

2 Analytical Framework

This section reviews three approaches to modelling the determinants of firm size and, by extension, the distribution of firms along the range from informal microenterprizes to large, formal sector employers. The first, "neoclassical" model of firm size due to Lucas (1978) makes the size choice a function the entrepreneur's managerial talent. In the second, a selection model based on Jovanovic (1982), the long run distribution of firms across size categories will depend on competitive pressures forcing inefficient firms out of the market. Finally, a third class of models focuses on the role of financing constraints in keeping small firms small.

We begin with the production side of the Lucas (1978) model of firm size.[2] The key underlying determinant of size in the Lucas model is the distribution of managerial talent among the population. Each individual in the economy is assumed to have some level of managerial talent, θ, drawn from a distribution $\Gamma(\theta)$. Production follows

$$y_{it} = \theta g[f(n_{it}, k_{it})] \tag{1}$$

where $f(.)$ is a standard production function employing capital and labor, couched within a managerial technology, $g(.)$, which is assumed to be concave. This concavity determines an optimal "span of control" for a manager with a given talent level. We measure this optimal span of control in employment terms

[2] The full Lucas model relies on general equilibrium effects in which the equilibrium wage rate determines whether it is optimal for an individual with a given talent level to become a manager or wage employee. Rauch (1991) presents an interesting extension of this framework in which wage differentials between the formal and informal sector determine the number and sizes of firms in each sector.

as $n_i^*(\theta_i)$.[3]

The second insight we wish to incorporate is due to Jovanovic (1982). Managers now receive only an imperfect, short run signal $\tilde{\theta}_{it}$ of their own underlying managerial talent (a.k.a, the long run efficiency of the firm, θ, without the time subscript). This signal also includes a mean zero transitory shock, ϵ_{it} which is independent across time such that

$$\tilde{\theta}_{it} = \theta_i + \epsilon_{it}.$$

These shocks matter in that they affect short run profits, but they also help to conceal the long run viability of the firm.

At the beginning of each period managers form an expectation of their talent, $\mathrm{E}(\theta_t)$ and choose their level of production scale of production, $\tilde{n}_{it}$. Managers anticipating a higher value of θ will choose to open larger firms. After observing their short run efficiency $\tilde{\theta}_{it}$ (i.e., their profitability) they update their expectations of next period efficiency $\mathrm{E}(\tilde{\theta}_{i,t+1}|\tilde{\theta}_{it})$ following Bayes' rule. As in the Lucas model, Jovanovic demonstrates the existence of some cutoff level θ^* such that when $\mathrm{E}(\tilde{\theta}_{i,t+1}) < \theta^*$ it will be optimal to exit the industry. In contrast, new entrants will be a random draw from the talent distribution $\Gamma_0(\theta)$. This systematic difference between the efficiency of entering and exiting firms is what drives the evolution of firm size.

Finally, patterns of firm growth, entry and exit may be determined not only by their underlying efficiency, but also by their access to financing. 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

$$n_{i,0} = \begin{cases} \min\{\tilde{n}_i, \omega\} & \text{with probability } p(\omega) \\ \\ \tilde{n}_i & \text{with probability } 1 - p(\omega) \end{cases}$$

This setup allows that some fraction of young entrepreneurs will be able to raise financing among friends and relatives, thus escaping the constraints otherwise predicted by their wealth. However, the probability $p(\omega)$ of being credit constrained is increasing in ω. Finally, because the model assumes that financing constraints are relaxed over time, firm size in the following period is always at the efficient level, $n_1 = n^*(\theta)$.

[3]Note that the Lucas (1978) model is essentially an exogenous growth framework: there is nothing endogenous to the model causing optimal firm size to change over time, nor firms to ever exit.

To review, the full-information, unconstrained optimal firm size in the neoclassical model, n_i^* is a function exclusively of the firm's underlying efficiency or managerial talent. Relaxing the assumption of full information, firms will adjust their preferred size $\tilde{n}_i t$ over time and possibly exit the industry as their realized profits provide them with information about their long term viability. Two important empirical predictions which emerge from this selection framework have frequently been noted to match well with the final stylized fact discussed in section 1.2:

1. The probability that a firm survives from one period to the next is increasing with its size. However, growth rates *conditional on survival* are lower for big firms.

2. The probability of survival increases with firm age, while growth rates conditional on survival decline.

Finally, models focusing on financing constraints suggest that in the absence of well functioning credit markets:

3. Actual firm size n_{it} will depend on the financial resources available within the firm. Initially, this can be proxied by owner wealth, ω_i.

4. Over time, financial constraints should be relaxed as profits become available to finance expansion. Thus, as time transpires the relevant measure of financing constraints may become the level of profits, π_{it} rather than initial wealth.

3 Empirical Model

This section elaborates a framework for testing the above predictions using the Ghanaian Industrial Census data and the panel data on the sample from the Ghana Manufacturing Enterprize Survey. We begin by presenting a basic decomposition of the shift in the firm size distribution into three components: (a) entry of new firms, (b) growth rates of existing firms conditional on starting size, and (c) exit rates. We then present a framework for investigating the underlying determinants of these three phenomena, drawing on the theoretical models from the previous section.

In analyzing the trend toward informal employment in Ghana, our goal is to understand the shift in the distribution of firms in period t, which we denote F_t, to the distribution F_{t+1}. For simplicity, we divide these distributions into q discrete groups so that we can represent F_t as a $q \times 1$ vector of densities.

Denoting the probability that a firm in size group a ends up in group b by p_{ab} we can define the $q \times q$ transition matrix M as a matrix of probabilities such that

$$F_{t+1} = MF_t \tag{2}$$

$$= (M^B + M^S + M^D)F_t. \tag{3}$$

The second line decomposes M into a diagonal matrix of entry (or birth) rates M^B, a matrix of transition probabilities conditional upon survival M^S, and another diagonal matrix of exit (or death) rates M^D:

$$M^S = \begin{pmatrix} p_{11} & \cdots & p_{1q} \\ \vdots & \ddots & \vdots \\ p_{q1} & \cdots & p_{qq} \end{pmatrix}, M^B = \begin{pmatrix} b_1 & & 0 \\ & \ddots & \\ 0 & & b_q \end{pmatrix}$$

and M^D is identical to M^B after replacing entry rates with exit rates. The diagonal elements of M^B (or, respectively, M^D) are birth (death) rates, defined as the number of firms entering (exiting) a given size class as a proportion of those observed in period t. Because the M^S matrix maps the distribution of surviving firms from one period to the next, its rows must some to one. This is not the case with the combined M matrix, however, which will incorporate entry and exit rates. In particular, the diagonal terms of M will be $m_{aa} = p_{a0} + p_{aa} + p_{0a}$, which will be greater than one if there has been net entry into a particular size class of firms.

In order to solve for these three matrices separately in an empirical application, we require not only data on the starting and ending distributions, F_t and F_{t+1}, but also on the distribution of firms which survived from period t to $t+1$ which we denote F_t^S and F_{t+1}^S respectively. Provided we can identify these distributions of survivors, we can write

$$F_{t+1} = M^B F_{t+1}^S, \tag{4}$$

$$F_{t+1}^S = M^S F_t^S \text{ and} \tag{5}$$

$$F_{t+1}^S = (M^S + M^D)F_t. \tag{6}$$

Note that equation 5 is implicitly a system of q equations with $q \times q$ unknowns, and thus yields infinite possible solutions. To identify the actual M^S matrix we rely on information tracking individual firms across time. After computing M^S, equations 4 and 6 can be solved directly for M^B and M^D. Our empirical estimates of each of these matrices are presented in section 4.

Armed with this decomposition, it is possible link the patterns of distributional change embodied in these matrices to more standard, regression-based techniques for studying firm dynamics. The disadvantage of regression-based techniques is the frequent need to impose fairly restrictive parameterizations on the data.[4] However, the non-parametric approach we have outlined so far is largely descriptive. The enormous advantage of regression based techniques is the ability to easily investigate the underlying determinants of entry, exit, and firm growth.

To see the link between the two approaches, consider each of the three submatrices above individually.

$$M^B: \quad n_{i,t=0} = n(\theta_i, \omega_i, p(\omega_i)) \tag{7}$$
$$M^S: \quad \Delta n_{it} = g(n_{i,t-1}, \theta_{i,t-1}, \pi_{i,t-1}) \tag{8}$$
$$M^D: \quad \lambda_{it} = \lambda(n_{i,t-1}, t, \theta_{i,t-1}, \pi_{i,t-1}) \tag{9}$$

We can imagine that the probabilities in each cell of these matrices are produced by an underlying causal model that is approximated by the corresponding equation on the right hand side. In the first line, the matrix of entry rates M^B reports the number of new firms which will enter each size category (divided by the number of existing firms in that category). We study the determinants of these entry patterns by identifying the owner characteristics (proxies for wealth and "managerial talent") which correspond to entry into each size class. Turning to the second line, equation 8 models the growth of existing firms conditioned on the initial level of employment. The predicted growth rates from this equation (and their corresponding confidence intervals) can be mapped directly into the transition probabilities which constitute the M^S matrix. Finally, equation 9 is a survival model of a firm's life span, conditional on its age and other characteristics. The predicted hazard rates emerging from this model can be used to calculate the exit probabilities along the diagonal of the M^D matrix, and to study the characteristics of individual firms which contribute to differential exit rates by size class.

This paper will restrict attention to the decomposition of the transition matrix M and estimation of the determinants of entry size, equation (7).[5] Op-

[4] For instance, studying firm growth in a regression model, in constrast to the non-parametric transition matrix estimated here, limits the possible pattern of distributional change to a stable distribution, convergence or divergence. More complex - such as convergence to a bimodal distribution which Quah (?) has identified in cross-country income data - are ruled out.

[5] This conference paper is an abridged form of a chapter from my Ph.d. dissertation. The full chapter, including estimation of all three empirical equations (7 - 9) is available upon request.

erationalizing this empirical model requires finding measures or proxies for both firm level efficiency and financing constraints:

$$\theta_{it} \approx \theta(educ_i) \tag{10}$$
$$p(\omega_i) \approx p(gender_i, age_i, exper_i, credit_i) \tag{11}$$

As our primary measure of firm level efficiency we rely on the extremely crude proxy of the owner or manager's level of education. To proxy the wealth level and credit market access of the entrepreneur we use gender, age, and work experience. We also have direct survey reports on whether entrepreneurs had access to either formal or informal credit markets at the time of starting their business.

4 Entry, Exit, and Transition Matrices

Industrial evolution can be decomposed into two components: the growth (or decline) of individual firms, and the possibly non-random selection of firms. In this subsection we use data from two rounds of the Ghanaian Industrial Census to examine the relative importance of these forces in explaining the trend to smaller firm size.

Linking the two rounds of the Ghana Industrial Census provides a rare look at industrial evolution in Africa during the structural adjustment period. Simple comparison of the two cross-sections provided by the Ghana Statistical Service reveals the dramatic downward shift in firm size distribution documented in section 1.1. In this section we push this analysis one step further by creating a panel of firms which we can track between the two waves of the census. This will allow us to decompose the shift in the firm size distribution into differential entry rates, growth rates, and exit rates between (large) formal and (small) informal firms.

As already noted, in order to perform this decomposition we require data on F^S_{t+1} and F^S_t. Because the 2003 census provides information on firm age we can directly observe F^S_{t+1} by calculating the distribution of firm sizes (in 2003) for all firms which existed at the time of the 1987/88 census. However, calculating F^S_t requires that we observe the size of these same firms in 1987. Unfortunately there is no unique identifier linking the firms in the two datasets. Instead, we have attempted to match firms on three criteria: (a) three-digit ISIC codes, (b) region and/or city, and (c) firm name. Applying these criteria yields a panel of 236 firms.

Table 3 reports our estimates of the transition matrix M^S for the panel of survivors from 1987 to 2003. Two key points emerge from the table. First, there is considerable mass on the diagonals and the upward and downward movements which do occur appear to balance fairly evenly, indicating mean growth rates (over 16 years) in the vicinity of zero. This finding is corroborated by the annual panel of firms from the GMES data where the mean annual growth rate is insignificantly different from zero. Second, while a nontrivial number of firms do move size classes, there are relatively few large movements. In particular, no firm is observed to move from the smallest to the largest category, indicating the rarity with which informal microenterprizes grow into large formal sector firms.

A third, somewhat anomalous feature of the transition matrix in table 3 is seen in the last line, where we calculate the long-run, ergodic distribution of firm sizes implied by the matrix. Starting with the 1987 distribution of firms the ergodic distribution is calculated by iterating M^S until the densities in each of the q cells remain constant. As seen in the table, the long-run distribution to which surviving manufacturing firms in Ghana appear to be converging is bimodal, with significant mass in the microenterprize sector and another peak in the 200-499 employee size class. Mathematically, this bimodal outcomes results from the relatively lower mass found on the diagonal terms of M^S corresponding to the intermediate size classes. However, due to the low number of observations in our census panel, this result may be fragile to a few outliers.

To investigate the robustness of our estimated pattern of distributional change, we also estimate M^S using an independent data source – the panel of firms included in the GMES sample. Transitions are based on 889 year-on-year growth rates. These growth spells emerge from an unbalanced panel of 264 firms spanning 1991 to 2002. The transition matrix which emerges from the GMES data, Table 4, is similar that from the Census data in that growth rates are largely symmetric across categories and centered around zero (the average annual growth rate of employment in the sample is insignificantly different from zero). However, the GMES sample exhibits significantly more churning. Iterating this matrix over 16 years for comparability with the census data (not shown), produces a picture of much greater churning between size classes. The net result of the differences in our two estimates of M^S can be seen by comparing the ergodic distributions implied by each. The long run distribution of firms implied by the GMES data has considerably more mass in the small firm sector (5 to 19 employees) relative to the census. This is probably the result of short run growth by young, small firms which generally fail to survive the

16 year time span necessary to appear in the census panel. The other contrast is the absent of the bimodal pattern implied by the census transitions. The transitions observed in the GMES imply a smoothly tapering right tail to the firm size distribution, with considerably less mass among large firms in the long run than currently observed.

So far we have restricted our attention to the distribution dynamics for surviving firms. Based on our calculations of F^S_{t+1} and F^S_t and the estimates of M^S, we can solve for the transition matrices as described in the previous section. Expressions 3, 5 and 6 solve to yield

$$\begin{aligned} M^B &= [\text{diag}(F_{t+1} - F^S_{t+1})][\text{diag}(M^S F_t)]^{-1}, \text{ and} \\ M^D &= [\text{diag}((M^S - M^D)F_t - F_{t+1})][\text{diag}(M^S F_t)]^{-1} \end{aligned}$$

where the diag() operator maps a $q \times 1$ vector into a $q \times q$ diagonal matrix. As the 1987 census only reports firm level employment in the form of 9 size categories, we set $q = 9$. The bounds of these 9 cells are given in table **??**.

Table 5 reports calculations of gross firm entry and exit rates. The final two columns of the table correspond to the diagonal entries of the M^D and M^B matrices respectively.[6] Unsurprisingly, both entry and exit rates are much higher among small firms. Each year the entering cohort of new microenterprizes represents 19% of the previous year's population of firms. Meanwhile, establishment of new large enterprizes has effectively ceased in Ghana.

So far in this section we have assumed that the parameters of interest (transition, birth and death rates) have been constant over 1987-2003 range. This would imply that at independence in 1957 there were fewer than 700 manufacturing firms in operation in Ghana, which appears wholly inconsistent with the limited information available from the 1962 industrial census.[7]

The assumption of a constant net entry rate is testable. Using the data on firm age from the 2003 census we calculate the net entry rate in year t as the number of firms observed in 2003 which were born in that year $C_{03,t}$ over the total number of firms born in earlier cohorts.

$$\text{net entry}_t \equiv b_t - d_t = \frac{C_{03,t}}{\sum_{s=-\infty}^{t-1} C_{03,s}}$$

[6]Note that these calculations are preliminary. They were done on the assumption of zero transitions - i.e., ignoring the M^S matrix. As a result, size categories who were net recipients of surviving firms might report negative exit rates, as is the case for firms with 200 to 500 employees.

[7]The 1962 census records 296,700 persons engaged in manufacturing. However, this number includes household enterprizes, so is not directly comparable with the 1987 and 2003 censuses.

The age range in the 2003 census is 0 to 102 years, however we restrict ourselves to firms aged 0 to 30 because sample sizes for older cohorts are extremely small. We test whether this rate has been constant by regressing the calculated net entry rates on a logarithmic trend $\ln t$. We find

$$\text{net entry}_t \quad = \quad \widehat{-38.7} + \widehat{5.1} \ln t + \hat{u}_t, \qquad \text{obs.} = 30$$

where we reject the absence of a trend effect with a p-value of 1.1%. These estimates imply that the rate of net entry doubled between 1980 and 2000, from approximately 8% to 16% per annum across all size categories.

5 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 we divide into the following categories: younger than 1 year, 2-4, 5-9, 10-19, 20-29, and 30 years or older. Figure 3 plots nonparametric estimates of the firm size distribution in logs by age category using the cross-section of firms in 2003 Census.[8] Consistent with the life-cycle pattern, older firms are consistently larger than those in later cohorts. For comparison, we also replicate Table 3 from Cabral and Mata (2003) who provide a similar breakdown for the population of Portuguese manufacturing firms

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 (2003) demonstrate a simple method of distinguishing growth from selection using two rounds of a census of Portuguese manufacturing firms, which they argue are fairly representative of developed country data sets in terms of their size distribution and evolution. Figure 4 reproduces three size distributions for the cohort of Portuguese firms which entered in 1984, as presented by Cabral and Mata (p. 1079). The leftmost curve plots the distribution of all entrants in 1984, a total of 2,651 firms. Of this 1984 cohort,

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

only 1,031 were still operating in 1991. Figure 4 also plots the size distribution of these surviving firms, both at the time of their birth and seven years later in 1991. 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 figure shows that for Portuguese manufacturing firms, selection (by size) 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 (1982).

The bottom panel of Figure 4 attempts to replicate the test suggested by Cabral and Mata using the Ghana Industrial Census data. [9] As seen in the figure, the pattern of growth and selection in this sample is almost precisely the opposite of that observed in Cabral and Mata's data on Portuguese firms. 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. [10]

6 Starting Size & Characteristics of Entrepreneurs

The vast majority of job creation in Ghana's manufacturing sector over the 1987-2003 period occurred through the entry of new firms. Based on the numbers presented in the previous section, entry of new firms accounted for all net job growth in the sector. From a labor market perspective, the policy challenge posed by this trend is thus not a lack of new jobs (much less of new firms), but rather that these jobs which have been created are overwhelmingly in the informal sector where wages are extremely low.

This section uses recall data from firms in the GMES sample to study the determinants of firms' starting size measured in employment terms. Upon their initial interview (either in 1991 or thereafter for firms which entered the sample in subsequent years) entrepreneurs or managers were asked about both their

[9] Unfortunately, firm age is not reported in the 1987 census, so we are unable to identify the 1987 cohort of entrants. Instead, we 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, we were able to match 236 firms by ISIC code, region, and firm name.

[10] It is important to note that the panel of 236 survivors which we identify represents only about 10% of the firms in the 2003 census which claimed to have entered in 1988 or earlier. Comparing these 236 to the larger population of survivors, average firm size is somewhat larger for those we were able to match. However, this will undermine our conclusion in the text only if these 236 firms grew significantly more slowly than the average for the population of survivors.

personal characteristics and the characteristics of the business at the time of entry.

What will determine firm size at start-up? The basic neoclassical model (Lucas 1978) suggests that micro variation in firm size will depend entirely on underlying efficiency, θ_i. In contrast, the main testable prediction of the financing constraints model presented in the previous section is that the impact of owner age (as a proxy for financial constraints) should diminish over time, while owner education (as a proxy for managerial skill and long run efficiency) should not. Cabral and Mata (2003) confirm this pattern using data from a census of manufacturing firms in Portugal.

Unfortunately we have access to only crude proxies for both efficiency and wealth endowments at the time of entry. While it is possible to estimate underlying efficiency for existing firms, we rely on the owner's level of education as a proxy for the efficiency (or 'managerial talent' in Lucas' terms) of firms which have yet to produce anything. Turning to financial constraints, Cabral & Mata (2003) have recently used owner age as a proxy for savings and access to capital. We follow this suggestion, but also use a somewhat more direct measure of credit access based on a survey question on the source of initial financing for the business: own savings, relatives and friends, formal or informal credit. Thus we estimate

$$\begin{aligned} n_{i,t=0} &= n(\theta_i, \omega_i) \\ &= \alpha_0 + \alpha_1 educ_i + \alpha_2 age_i + \alpha_3 credit_i + u_i \end{aligned}$$

If cash flow from profits allows firms to escape the financing constraints which initially limited their size, the size and significance of the α_2 and α_3 parameters should decline over tiem. Table 6 shows relatively weak evidence of such a pattern for Ghana. Each column regresses the log of firm size on various owner characteristics at a given point in the firm's life cycle. Column 1 models the determinants of starting firm size. The effects of gender, education, and owner's age are all significant both statistically and economically. Men start firms which are on average 66% larger than do women, even after controlling form men's higher average level of education. Age has a similarly dramatic effect. Holding other variables at their median values, the predicted starting firm size for a 20-year old entrepreneur is 4 employees, while for a 40-year old it is 9 employees. This coefficient is more than twice as large as that estimated by Cabral and Mata on Portuguese data.

However, the results in columns 2 to 4 provide mixed evidence on the extent to which the impact of owner age on firm size erodes over the firm life cycle. While the point estimate on owner age drops by half between columns 1 and 2, it is not estimated with sufficient precision for this change to be significant. A similar result is obtained by interacting firm age with owner age in column 4 where firms of all ages are pooled. In sum, there is some suggestive evidence in the GMES data that credit constraints play a role in determining starting size. However, as far as this inference is valid, it appears that for African firms in contrast to their European counterparts, these constraints are not automatically relaxed over time.

7 Relation to Existing Work

The decomposition of the trend toward informality carried out in section 4 was primarily descriptive. However, equations (7) - (9) illustrated how the results of this decomposition could be related to more standard empirical frameworks for analyzing the underlying determinants of firm dynamics. In section 6 we pursued one such avenue, focusing on firm entry as it is entry which currently appears to be driving the trend toward informality in Ghanaian manufacturing. However, it may be equally important to analyze what we did not observe in section 6 - namely, job creation within existing firms. Why haven't small, informal firms been able to grow through the size distribution over the last two decades? To answer this question we turn to a review of earlier studies which have estimated equations similar to the growth and survival models suggested by our framework in section 3 (equations 8 9).[11]

In interpreting these results we draw on the analytical framework discussed in section 2, which focused on the contrast between the roles of uncertainty and financial constraints in determining patterns of firm growth. In the Jovanovic (1982) framework, growth rates will decrease with both firm age (conditional on size) and firm size (conditional on age). Firms are assumed to have perfect insurance and access to credit markets, so financial variables should not affect the growth path. In contrast, financial variables may become central determinants of size and growth if firms are credit constrained.

Growth Determinants. Previous work using data on African manufacturing firms has found that, inasmuch as growth rates differ at all between size classes, larger firms tend to grow faster (Van Biesebroeck 2005, Sleuwaegen and

[11] Soderbom & Bigsten (2005) provide a more comprehensive overview of empirical work on firm level data sets in Africa.

Goedhuys 2002). This is consistent with our finding that small microenterprises fail to grow into large firms.

What determines this generally slow and possibly divergent pattern of growth? One set of explanations which can be ruled out are those relating to efficiencies of scale. Using the GMES data which we have drawn on here, Soderbom & Teal (2004) find that the underlying production function facing Ghanaian manufacturing firms exhibits constant returns to scale. Furthermore, Soderbom & Teal (forthcoming) find that large firms do not experience more rapid TFP growth.

A second, commonly invoked explanation for slow firm growth in Africa is a missing market for credit and insurance in the small-scale, informal sector. Existing evidence is more favorable to this story. Drawing on manufacturing surveys from six African countries, Bigsten et al (2003) report that 64% of micro firms ($\leq$ 5 employees) and just 10% of large firms ($>$ 100 employees) were credit constrained in the sense of having a demand for loans at market rates for which they were rejected or did not apply in anticipation of rejection. There is also evidence linking such constraints to firm growth. Fisman (2001) finds that access to trade credit reduces the probability of input shortages and thus may contribute to firm level efficiency. Soderbom & Teal (forthcoming) measure the impact of cash constraints on firm growth, drawing on a model specification pioneered in the empirical literature linking cash flow to firm level investment. They include the lagged level of firm profits in a model of factor input growth and find a significant positive effect, consistent with the view that financial constraints impact on growth.

Firm Survival. In addition to growing slowly conditional upon survival, entering cohorts of microenterprises in Ghana's manufacturing sector also exit rapidly. From an aggregate perspective, this would be less worrisome if firms which died were particularly inefficient. Indeed, the dominant theoretical paradigm in contemporary industrial organization views firm churning as a central component of productivity growth. However, it is unclear whether or not this positive selection process applies to Africa's informal sectors.

The key result in the existing empirical work on firm survival in Africa is actually a non-result: there is very little evidence that efficiency enables small firms to survive. A number of recent studies (Van Biesebroeck 2005, Soderbom, Teal, and Harding forthcoming, Frazer 2005) find that firm size is the only robust determinant of survival among Africa firms. Soderbom & Teal, for instance, estimate a probit model of firm exit using panel data on firms in Kenya, Tanzania and Ghana, and find that while there is some evidence that more productive firms survive longer in the large-scale sector, such a positive selection effect is completely absent among smaller firms.

To summarize, consider two patterns of job creation or "firm life-cycles" which we might observe in the data. On the one hand is the stylized picture presented by the Jovanovic selection framework: firms universally start small. Those which are highly efficient survive and grow, while the mass of less efficient firms dies off early in the life-cycle. On the other hand is a model of informality as a persistent state resulting from market failures. Enterpreneurs facing financing constraints hire fewer workers than the optimal level and fail to expand over time. Furthermore, lacking the insurance provided by credit markets, even relatively efficient small firms succumb to transitory shocks, undermining the productivity enhancing effects of competitive pressures. Clearly these two models of industrial evolution in Africa have starkly different implications for how we should interpret the explosion of micro firms documented above. Viewed through the lens of the Jovanovic model, the mass of new microenterprises which have emerged in Ghana over the last two decades might be seen as a harbinger of industrial expansion and productivity growth. Our analysis and earlier studies on African firms suggest a less optimistic scenario. Rather than a "baby-boom" of small firms which will grow into large scale employers, the current trend appears to constitute a structural shift toward smaller scale, lower wage jobs.

8 Conclusions

Wage employment may contribute to raising overall incomes by one of two general patterns: (1) increases in the wage rate for a given set of workers and a given composition of firms, or (2) employment expansion drawing workers in from low- to high-wage sectors. This paper has focused on the second route, and shown that at present much of Africa is headed in precisely the wrong direction.

Where data is available, the share of the informal sector in urban African labor markets appears to be growing rapidly. This trend is potentially ominous for a number of reasons: for a given level of total employment, a smaller firm size distribution will likely imply lower wages, reduced exports, and lower productivity growth potential for African economies.

By tracking firms over time through two waves of the Ghana Industrial Census we have been able to test the relative importance of firm growth versus non-random firm failure in producing a downward shift in firm size. We find a stark contrast with recent results from a developed economy. In both cases older cohorts of firms are significantly larger than new entrants. However, in European data this is primarily due to firm growth over the life cycle, whereas in Ghana we show that this effect is entirely due to the short lifespan of microenterprises.

Examining employment growth within individual firms, transition matrices from the census show that firm level employment growth has been negligible. Literally zero micro firms are observed rising to the upper portions of the size distribution.

The trend toward informal employment in Ghana is almost entirely a story of new firm entry. Entry of large firms has effectively ceased in this economy while microenterprizes have proliferated. The gap between entry and exit in the small firm sector is quite large even by developing country standards. Unfortunately, given the low wages in the microenterprize sector and the rarity with which these firms move up through the size distribution, there is little prospect for this current shift in Ghana's industrial structure to contribute to rising incomes for a significant number of workers.

References

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., and et al. (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.

Calves, A. E., and B. Schoumaker (2004): "Deteriorating Economic Context and Changing Patterns of Youth Employment in Urban Burkina Faso: 1980-2000," World Development, 32(8), 1341–54.

Fisman, R. (2001): "Trade Credit and Productive Efficiency in Developing Countries," World Development, 29(2), 311–21.

Frazer, G. (2005): "Which Firms Die? A Look at Manufacturing Firm Exit in Ghana," Economic Development and Cultural Change, 53(3), 585–617.

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

Kingdon, G. G., and J. Knight (2004): "Unemployment in South Africa: The Nature of the Beast," World Development, 32(3), 391–408.

Krishnan, P. (1996): "Family Background, Education and Employment in Urban Ethiopia," Oxford Bulletin of Economics and Statistics, 58(1), 167–83.

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

Mazumdar, D. (2002): Wages and employment in Africa, With Ata Mazaheri. Ashgate, Making of Modern Africa series. Aldershot, U.K. and Burlington, Vt.

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

Sleuwaegen, L., and M. Goedhuys (2002): "Growth of Firms in Developing Countries, Evidence from Cote D'Ivoire," Journal of Development Economics, 68(1), 117–35.

Soderbom, M., and A. Bigsten (2005): "What have we learned from a decade of manufacturing enterprise surveys in Africa?," Discussion paper.

Soderbom, 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.

Soderbom, M., F. Teal, and A. Harding (forthcoming): "The Determinants of Survival Among African Manufacturing Firms," Economic Development and Cultural Change.

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

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

A Data Appendix

As discussed in the text, the data on Ghanaian manufacturing firms was taken from two separate sources: two waves of the Ghanaian Industrial Census (1987 and 2003) and survey data on a sample of firms collected by the Centre for the Study of African Economies, Oxford.

A.1 Census Data

The second and third Ghana Industrial Censuses 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). The use of comparable variable definitions across the two surveys (e.g., the definition of establishments as all non-household enterprizes, the use of ISIC sector classifications, etc.) and the comprehensive nature of the census data offers a unique opportunity to compare the firm size distribution in an African economy at two points in time. Unfortunately for our purposes, the first Ghana Industrial Census conducted in 1968 did not distinguish between household enterprizes and business establishments, making comparison with the latter two rounds impossible.

The variables which are common to the 1987 and 2003 censuses are limited to the following:

- **establishment name.**
- **location.** Region and town.
- **4-digit ISIC code.** The 1987 Census uses ISIC Rev. 2, while the 2003 Census uses ISIC Rev. 3. Because of the difficulties in converting codes between revisions, it is only possible to create comparable sector codes at the 3-digit level.
- **persons engaged.** For the 2003 census we have the number of persons engaged for each establishment. However, for the 1987 census we only have this precise measure for firms with fewer than 10 employees. Otherwise, 1987 firms are grouped into size categories by the number of persons engaged: 10-19, 20-29, 30-49, 50-99, 100-199, 200-499, 500+. More detailed information was collected but apparently destroyed. However, the official census report does enable use to know the average firm size within each size category.

In addition, we also have a variety of additional information on firms in 2003 only, including:

- **Year of establishment.**
- **Employees** This number is restricted to paid employees and appears to differ from the "persons engaged" measure inasmuch as firms use apprenticeship labor which is generally unpaid.
- **Gross output.**
- **Input costs.**
- **Capital stock.** This measure is based on manager reports of the present value of machinery.
- **Total wages.**

A.2 Survey Data

The Ghana Manufacturing Enterprize 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 CSAE, 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 Enterprize Development (RPED) organized by the World Bank. The surveys have been funded by the Department for International Development of the UK Government and the CSAE is funded by the Economic and Social Research Council of the UK.

The obvious disadvantage to the GMES data (relative to the Census) is its much more limited coverage. Initially 200 firms were surveyed in each of 10 subsectors of manufacturing: food processing, drinks (distilleries), bakeries, garments, textiles, wood (lumber mills), furniture (non-metallic), chemicals, metal products (primarily welding shops producing rod-iron fences, etc.), and machinery. The sampling frame deliberately selected a disproportionate number of large firms in order to enable statistical analysis of all size classes (based on the 1987 census, a random sample of 200 firms would have been expected to include only 5 firms with over 100 employees).

The overwhelming advantages of the GMES data are essentially twofold. First, the survey presents a wealth of information on the firms in the sample, covering topics such as sources of finance, import and export behavior, prices, human capital of workers and management, taxes and the regulatory environment. The second advantage of the GMES is its panel structure. 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.
Selected Variable Definitions

- real profits per employee, π/L. Gross revenues minus wages, material input costs and indirect costs, deflated by a firm specific cost index. Measured in 1991 Ghanaian cedis, divided by 10,000 in the regressions.
- imports. Percentage of inputs which are imported.
- exports. Percentage of output which is exported.
- owner age and education. Values are reported for the owner or entrepreneur of small firms and the managing director of corporations. For state owned firms this information is not available. Instead, the mean value in the sample (49 years old, 11 years education) is imputed and a state ownership dummy is included whenever this variable is used in the analysis.

B Tables & Figures

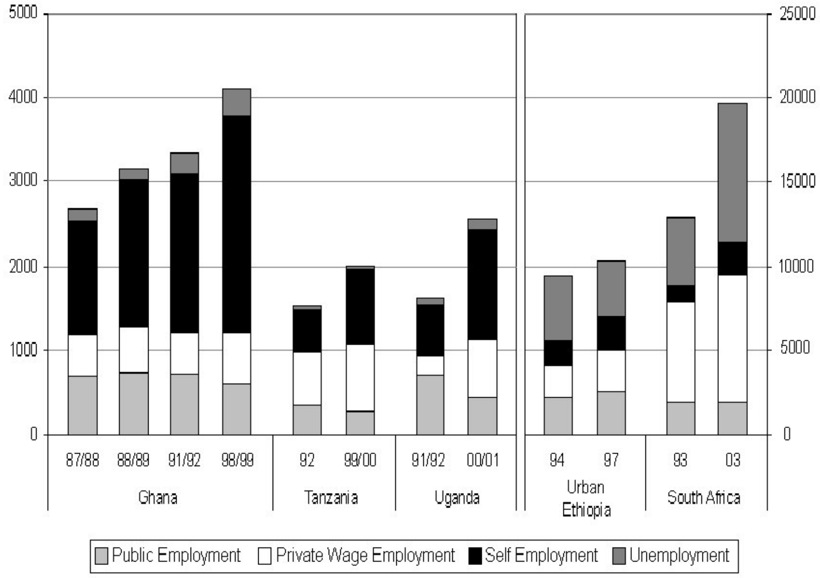


Figure 1: The pattern of employment growth in 5 African economies

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: Median Firm Characteristics by Size Category

	Micro	Small	Medium	Large
Levels Measures (Means)				
Wage (US$/mo.)	22.60	26.50	60.58	109.92
Labor Productivity (US$/emp-yr)	4,364	4,049	6,991	14,661
Capital-Labor Ratio (US$/emp)	1,733	2,757	8,188	16,985
Implied cost of capital (% p.a.)	1,780	390	80	50
Exports (% output)	2.51	3.43	7.98	26.2
Growth Measures (Medians)				
Employment Growth	-1.54	-0.357	-0.749	0
Output Growth	-2.48	-3.43	1.32	0.506
Labor Productivity Growth	-2.33	-0.831	2.41	-3.12
Volatility Measures (Median)				
Price Volatility	0.735	0.829	0.681	0.692
Output Volatility	0.581	0.52	0.479	0.359

Note: Size categories – micro (1 - 10 workers), small (11 - 30), medium (30 - 100), and large (> 100) – are defined using firms' average values over the sample. Monetary values are expressed in 1991 US$. Wage is the monthly US$ wage rate based on firm reports. Cost of capital is a proxy for the annual interest rate available to the firm, as described in the text. Growth is computed as the average annual percentage growth rate over the available sample for each firm. Volatility measures are based on coefficients of variation computed over time for a given firm.

Table 3: Transition Matrix by Size Category, Census Data: 305 firms identified in 1987 & 2003

	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+	Total
1 to 4	54.5	27.3	18.2	0	0	0	0	0	0	100
5 to 9	34.2	41.1	15.1	6.8	1.4	1.4	0	0	0	100
10 to 19	11.9	33.3	23.8	11.9	9.5	7.1	2.4	0	0	100
20 to 29	0	16.7	41.7	8.3	25.0	0	0	8.3	0	100
30 to 49	7.7	0	7.7	15.4	38.5	7.7	7.7	15.4	0	100
50 to 99	0	0	11.8	5.9	23.5	41.2	0.0	11.8	5.9	100
100 to 199	0	0	8.7	13.0	8.7	21.7	8.7	30.4	8.7	100
200 to 499	0	0	0	0	0	6.7	20.0	40.0	33.3	100
500+	0	0	0	0	0	0	0	50.0	50.0	100
ergodic	20.5	18.8	12.7	6	7.5	6.2	4.3	15	8.9	100

The first column lists size categories in 1987 and the first row lists size categories in 2003. Each cell reports the percentage of firms in a given row (1987) which ended up in a given column (2003). In total, 71 firms moved up in size class, 72 firms dropped down, and 82 firms remained in the same category.

Table 4: Transition Matrix by Size Category, GMES Sample Data

	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+	Total
1 to 4	78.6	18.8	2.1	0.5	0	0	0	0	0	100
5 to 9	14.4	66.4	17.5	1.4	0.3	0	0	0	0	100
10 to 19	1.4	15.6	68.9	12.1	1.7	0.3	0	0	0	100
20 to 29	0	1.6	22.6	54.8	18.8	1.6	0.5	0	0	100
30 to 49	0	1.8	3.2	12.2	67.4	15.4	0	0	0	100
50 to 99	0.5	0	0.9	1.4	14.6	75.0	7.5	0	0	100
100 to 199	0.6	0	0	0.6	1.2	11.2	77.6	8.8	0	100
200 to 499	0	0	0	0	0	0	9.4	85.5	5.1	100
500+	0	0	0	0	0	0	2.4	19.5	78.0	100
ergodic	14.2	18.5	20.2	10	12.5	11.6	6.9	6.1	1.4	100

Table 5: Entry & Exit by Size Class (Census Data)

	No. Firms			Total %	Annual	Annual
Size	1987	2003	Survivors	Survivors	Exit Rate	Entry Rate
1 to 4	2947	11767	1301	44.1	5.0	14.0
5 to 9	3438	5843	928	27.0	7.9	11.2
10 to 19	744	1812	444	59.7	3.2	8.9
20 to 29	196	420	158	80.8	1.3	6.2
30 to 49	142	343	116	81.6	1.3	6.9
50 to 99	128	247	84	65.5	2.6	6.8
100 to 199	85	104	41	48.0	4.5	5.7
200 to 499	56	67	60	107.5	-0.5	0.6
500+	49	31	24	49.2	4.3	1.5

Source: Author's calculations based on the 1987 and 2003 Ghana Industrial Censuses. Entry and exit rates for each size class are computed on the assumption of zero transitions.

Table 6: Firm Size and Entrepreneur Characteristics

	Separate Regressions by Firm Age Group			
	Start	1 to 10	> 10	All Firms
	(1)	(2)	(3)	(4)
male owner	.506	.667	.172	.337
	(.193)***	(.124)***	(.088)*	(.072)***
owner educ	.060	.081	.070	.101
	(.018)***	(.012)***	(.008)***	(.013)***
ln (owner age)	1.404	.738	.815	.879
	(.428)***	(.225)***	(.265)***	(.188)***
firm age		.029	.008	.016
		(.024)	(.008)	(.053)
(owner educ) $\times$ (firm age)				-.002
				(.0007)***
ln (owner age) $\times$ (firm age)				.0009
				(.011)
Obs.	137	381	809	1202

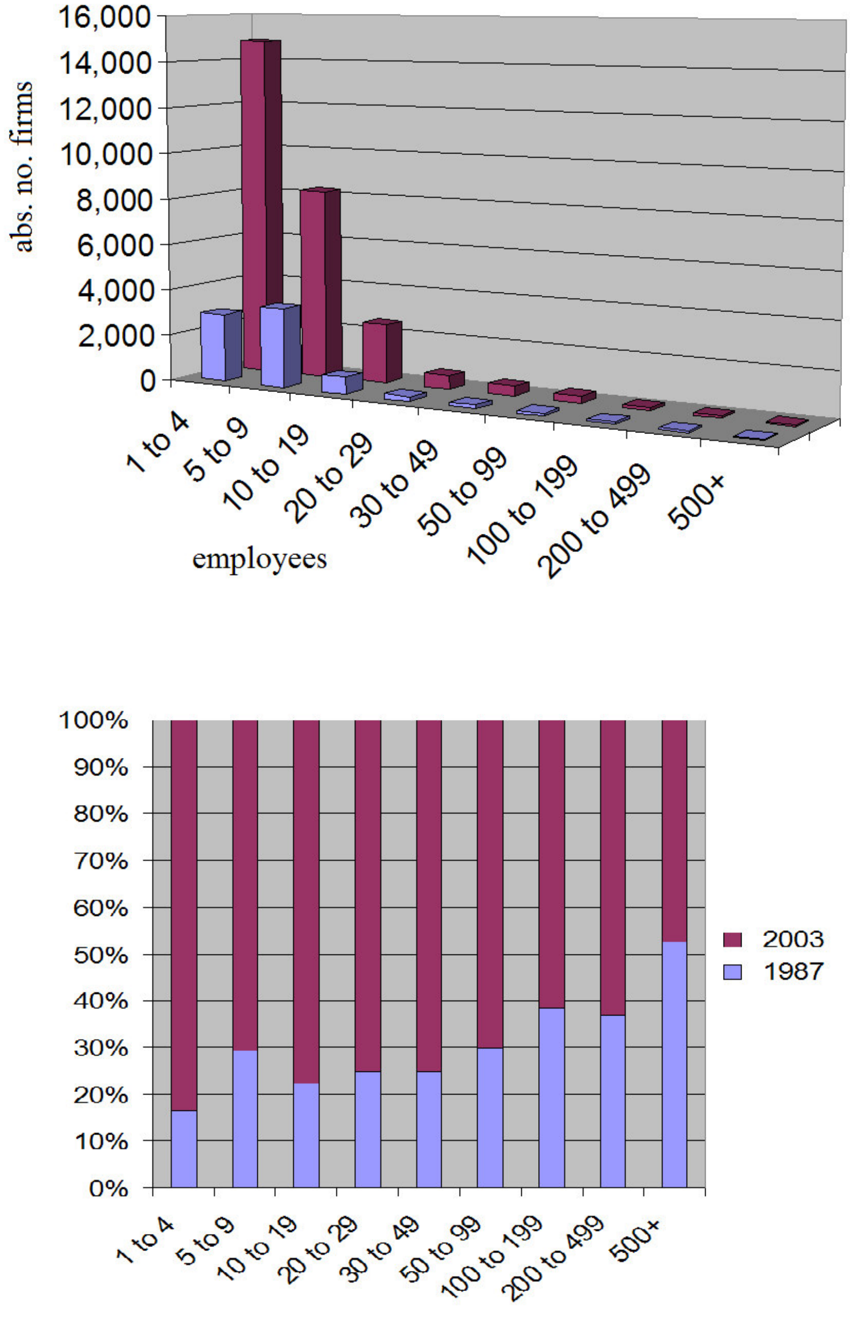


Figure 2: No. of Enterprizes by Size Category: 1988 & 2003

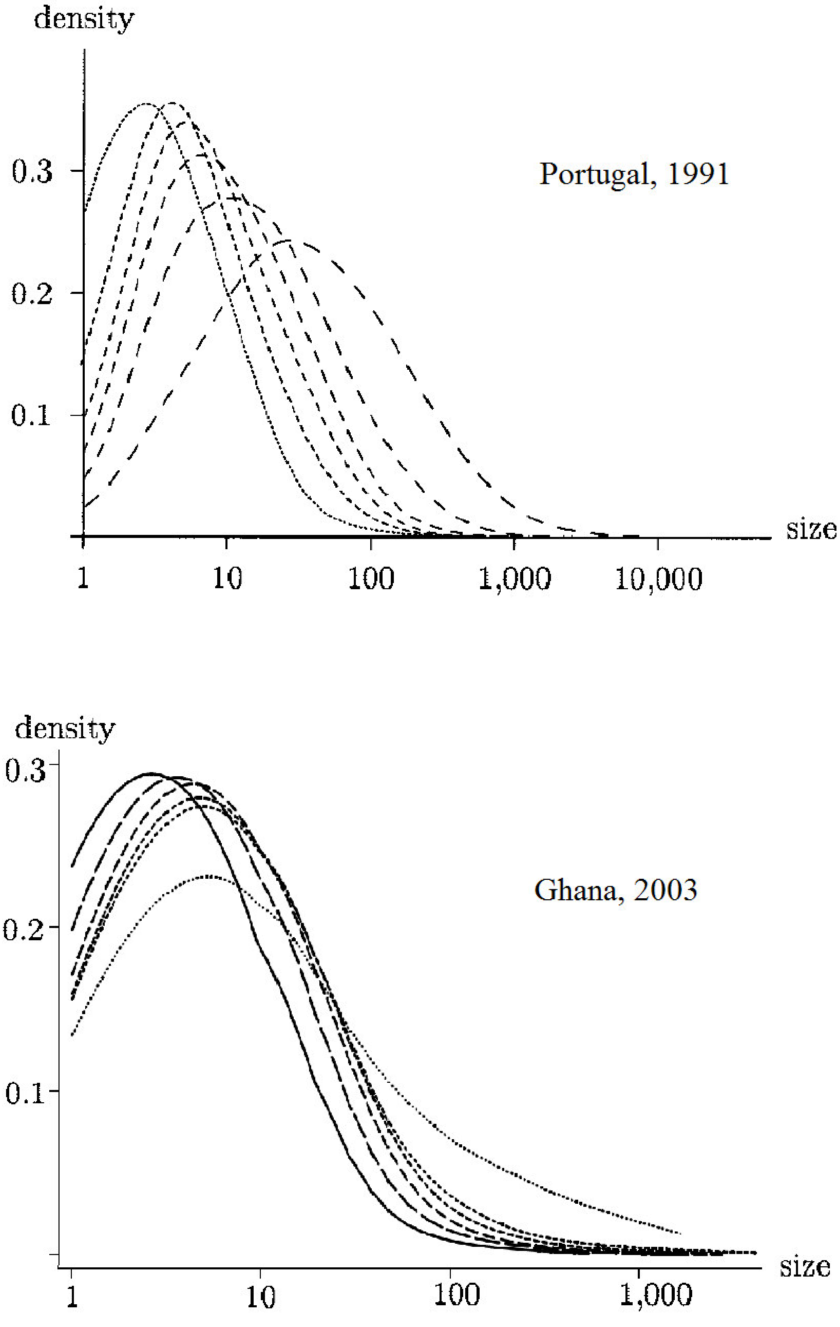
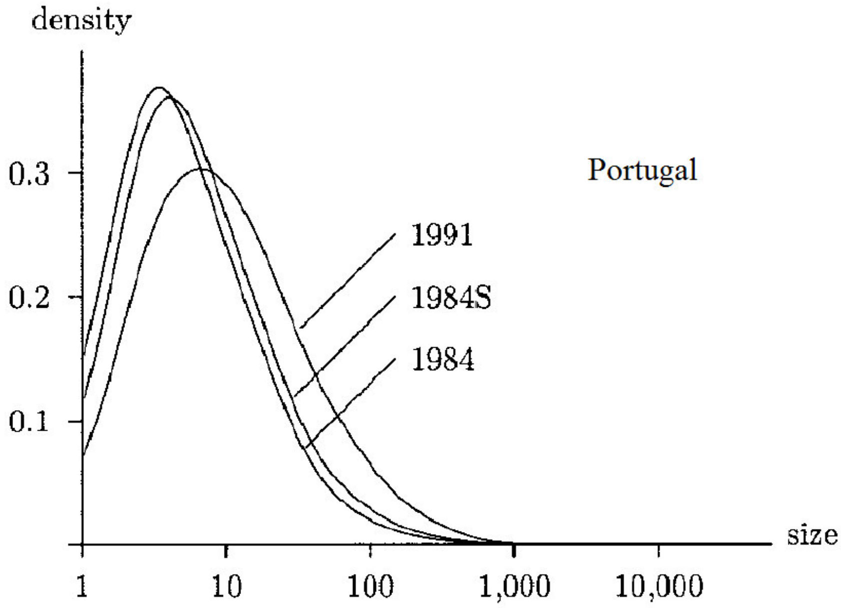


Figure 3: Size Distribution of the 2003 Population by Age Category: Longer lines denote younger firms



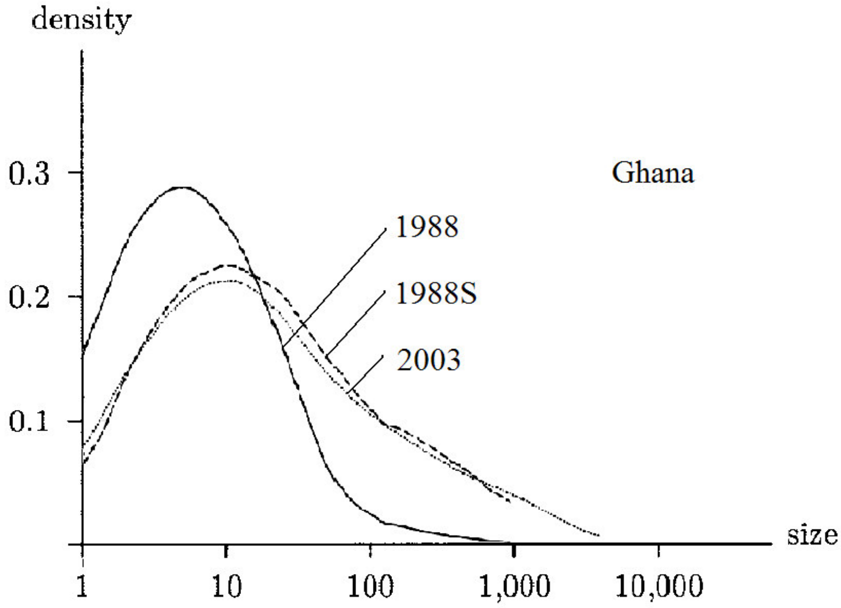


Figure 4: Opposite Patterns of Growth and Selection. Top panel: Portugal, 1984 Cohort of Entrants. Bottom Panel: Ghana, 1987 Population of Firms.