The Small, the Young, and the Productive: Determinants of Manufacturing Firm Growth in Ethiopia

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I. Introduction

The growth of manufacturing firms has been the focal point of most industrial policies. In Africa, large firms have been criticized for not creating enough jobs, while micro and small firms have been identified as the main sources of industrial job creation (Biggs and Srivastava 1996). However, this argument is empirically controversial in sub-Saharan Africa (henceforth SSA; Bigsten and Söderbom 2006), and needs further investigation.

So how does growth vary across firms? Do small firms grow faster than large firms? What other attributes affect firm growth? These are important concerns for countries trying to industrialize and create jobs. Understanding the relationship between growth and size is of particular interest for SSA countries, given that most firms are small. A point of departure in the firm growth literature is the Law of Proportionate Effect (LPE), or Gibrat's law. According to this law, the growth rates of firms are independent of their size. Most recent studies in developed countries have found a significant negative relationship between firm growth and firm size, which is evidence against Gibrat's law (Kumar 1985; Evans 1987a, 1987b; Hall 1987; Dunne and Hughes 1994; Caves 1998). Several studies have also found a negative relationship between firm growth and age (Evans 1987a; Hall 1987; Dunne and Hughes 1994).

However, the evidence on the association between firm growth and size in SSA manufacturing is mixed (Bigsten and Söderbom 2006). Mead and Liedholm (1998), Gunning and Mengistae (2001), and Sleuwaegen and Goedhuys (2002) reported a negative relationship between firm growth and size. Teal (1998) found for Ghana that the rate of growth is highest for medium-sized firms, while Harding, Söderbom, and Teal (2004) found no evidence of correlation between growth and size. Van Biesebroeck (2005) found that large

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firms grow more rapidly than small firms conditional on other covariates using data on nine SSA countries.[1]

This article extends the previous empirical studies on firm growth in SSA in the following ways: First, unlike all the previous studies on SSA, it relies on census-based panel data from Ethiopian manufacturing from 1996 to 2003.[2] Second, it explicitly addresses the statistical concerns in the growth-size models such as sample selection bias and regression to the mean. Third, using the special advantage of annual and longer panel data than earlier studies, it introduces a recently developed system generalized method of moments (GMM) method to control for the effect of unobserved heterogeneity and endogeneity in the firm growth-size relationship.

Overall, our empirical results indicate that size is inversely related to firm growth, implying that smaller firms grow faster than larger firms. This relation is robust after correcting for sample censoring and unobserved heterogeneity and is not affected by fluctuations or measurement errors in size. The negative relation between growth and age predicted by the learning process is found to affect only younger firms at the early stages of their life cycles. Labor productivity affects firm growth positively. This is consistent with the passive learning model prediction and provides evidence of market selection. Capital intensity, location in and around Addis Ababa, and public ownership also affect firm growth positively.

The next section presents a literature review on models of firm growth. Section III discusses data sources and background and provides a descriptive analysis. Section IV gives the basic econometric framework and empirical results. Section V introduces the system GMM method to control the effect of unobserved heterogeneity and endogeneity problems in the growth-size/age relation, and the last section summarizes the findings.

II. Literature Review: Development of Models of Firm Growth

According to the standard neoclassical theory, size is determined by the same factors that determine the long-term average cost of firms, such as technology and market size. In the long run the optimum size of rational firms should be at the point where the minimum cost is achieved. This means that in a

[1] The nine SSA countries covered in most of the above-cited studies are Kenya, Ghana, Zambia, Zimbabwe, Côte d'Ivoire, Ethiopia, Burundi, Tanzania, and Cameroon. Most of these studies are based on the database provided by the Regional Program on Enterprise Development survey conducted in the 1990s and organized by the World Bank.

[2] One obvious criticism of sample survey data in contrast to census data is that the theories of firm growth apply to the complete size distribution of firms in homogeneous-product industries (Evans 1987b).

perfectly competitive market, firms with a U-shaped average cost curve should grow until they reach the lowest point of the curve, which implies a narrow size distribution.[3] However, the scale corresponding to minimum cost need not be the same for different firms. Hence, the static cost theory provides no prediction on the size distribution and no explanation as to why the observed size distribution is skewed (Simon and Bonini 1958).

Consequently, the research interest shifted to the hypothesis that the usually observed skewed size distribution of firms was generated by a stochastic process. This line of argument is the basis for the LPE, or Gibrat's law. According to this law, growth is independent of current size, shows no heteroskedasticity with size, and the concentration of size distribution increases with time. Firms grow each year following random drawings from a distribution of growth rates, which means that small and large firms have identical growth chances.[4]

Two empirical implications of Gibrat's law have been tested. The first approach tests whether the limiting size distribution of firms belongs to the family of skewed distributions (e.g., lognormal, Pareto, Yule, etc.). The second one tests whether firm growth is independent of size by looking at the relation between firm size and growth over successive years.

Early studies in developed countries reported close to lognormal distributions with some skewness to the right, which supported Gibrat's law (e.g., Hart and Prais 1956; Simon and Bonini 1958). However, the power of this test is questioned since the relationship between growth rates and size is not explicitly investigated (Hall 1987). Therefore, most recent studies have tested directly the relation between growth and size and have found a negative relationship contrary to Gibrat's law (Kumar 1985; Evans 1987a, 1987b; Hall 1987; Dunne and Hughes 1994, among others).

The failure to find support for Gibrat's law led to the development of firm growth literature in two directions (Sutton 1997).[5] The first development shifted the emphasis from purely stochastic processes to classical economic

[3] Some other theories have been developed based on different assumptions of the scale of economies, increasing return, decreasing return, and constant cost curves (e.g., Hjalmarsson 1976). If the firms have market power, then the optimal size is determined by demand considerations, and in the case of constant returns to scale the size distribution is indeterminate.

[4] There are several versions of this stochastic theory. A weaker form of Gibrat's law states that expected firm growth is independent of firm size only for firms in a given size class (Simon and Bonini 1958). Jovanovic (1982) argues that Gibrat's law applies to mature firms and firms within the same age cohort.

[5] Cabral (1995) provides justification of the inverse relationship between growth and initial size, assuming that firms must incur a sunk cost upon entry. Thus, initially firms build only a fraction of their long-run optimal capacity. Since small entrants are more likely to exit than large entrants, it is optimal for small entrants to invest more gradually and thus experience higher growth rates than large ones.

maximization problems. This recent literature argues that systematic forces, such as efficiency, investment differences (in R&D, human, or physical capital), and other firm attributes, have important effects on firm growth.

According to Jovanovic (1982), the potential entrants are assumed to know the mean and standard deviation of the costs of all firms (efficiency) but not of their own. Firms update their prior expectations after entering through experience and eventually become certain about their true type. Those experiencing high costs (low efficiency) decide to exit, and those experiencing low costs (high efficiency) decide to expand (grow). This passive learning mechanism thus relates firm growth to firm-specific efficiency differences.

Jovanovic's model has other empirically testable implications in the context of the life cycle pattern of firms as well. First, the model predicts that firm growth decreases with age for a given size and that the variance of growth is larger among small and young firms. This is because, as a firm ages and grows more confident about its costs, the mean and variance of its growth rate should decrease. Second, the probability of firm exit decreases with size and age, as these variables are the result of the previous market selection process.[6]

The other direction of research that sought statistical reasons for the failure of Gibrat's law tackles problems such as sample censoring, heteroskedasticity, and regression to the mean. Mansfield (1962) was the first one to mention that the negative relationship between firm growth and size might be due to sample censoring. This is because failure is common among small firms, and thus the proportional rate of growth, conditional on survival, is smaller for large firms, leading to a downward biased estimate of the relationship between firm growth and size.[7]

In addressing the sample selection problem, two popular methods are usually employed. The first one is to apply sample selection models in which the growth equation and the survival equation are estimated jointly using the maximum likelihood method (Evans 1987a; Hall 1987). The second method, taken by Dunne, Roberts, and Samuelson (1989), is to group firms into all plants in operation at the beginning of each time period and all plants in operation that survive and compare the results from the two groups. In spite

[6] Ericson and Pakes (1995) emphasized the importance of "active learning" through competitive investment in productivity enhancement (i.e., investment in R&D or in human or physical capital). Some empirical studies have tested the active learning model by introducing investment variables, such as physical, R&D, or human capital, into the firm growth regressions (e.g., Hall 1987; Mazumdar and Mazaheri 2003).

[7] Exit or failure from the given sector might be due not only to actual shutdown but also to switching into other business or hiding into informality. Small firms are more likely to switch business line and shift into informality, with the latter being a big concern in developing countries.

of the difference in the methodologies to address the sample selection problem, these studies once again confirm that size and age are negatively related to firm growth, and the probability of firm survival increases with firm size.

Another statistical concern is that the usually observed negative relationship between growth and initial size might be spurious due to a problem of transitory low size. This problem arises whenever there are transitory fluctuations in size or whenever there are transitory measurement errors in observed size. Firms that have transitory low size will, on average, seem to grow faster than those with transitory high size. Davis, Haltiwanger, and Schuh (1996) proposed the use of average size rather than initial size as an explanatory variable in the growth regression, since the latter tends to exaggerate the growth of small firms. So far this problem has received little attention in empirical work.

Most previous studies that test Gibrat's law are based on cross-sectional regressions implicitly assuming that all sources of heterogeneity are fully reflected in the observed variables. However, the growth-size relationship can be affected by unobserved factors such as background and skills of the entrepreneurs, workers' skills, and other firm-specific factors. If these unobserved factors are correlated with the explanatory variables in the model, the pooled OLS estimation provides biased coefficients. Recent developments in panel data analysis such as fixed effects (FE) and GMM are used to control for unobserved heterogeneity.

In light of this background, this article tests the passive learning model, that is, the growth-size/age relationship augmented by productivity, capital intensity, and other firm-specific attributes using census data for Ethiopian manufacturing firms. Moreover, it explicitly addresses the statistical concerns in growth-size models such as sample selection bias and regression to the mean. It also devotes special attention to the potential problem of endogeneity in the growth-size relationship using a recently developed system GMM method.

III. Data, Background, and Descriptive Analysis

A. Data and Background

Ethiopia is one of the poorest countries in the world with a very narrow industrial base even by standards of sub-Saharan Africa. It is also one of the many countries that have been in transition from a command economy to a market-oriented one. In the era of military government (1975–91) the private sector was stifled by the confiscation of industrial establishments and restrictions imposed on the size of investment. After about 2 decades of centralized economic policy a new government took power in 1991, and it has undertaken

TABLE 1
GROWTH OF GDP AND SECTORAL SHARE, ETHIOPIA, 1994–2003

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
GDP growth	3	6	11	5	−2	6	6	9	2	−4
GDP per capita growth	0	3	8	3	−4	4	3	6	−2	−6
Industry value added (% of GDP)	10	9	9	10	11	10	9	11	11	10
Services value added (% of GDP)	35	34	33	37	43	42	43	43	47	47
Agriculture value added (% of GDP)	55	56	58	53	46	47	48	47	43	43

Source. *World Development Indicators, 2006* (World Bank 2006).
Note. GDP = gross domestic product.

TABLE 2
OUTPUT, EMPLOYMENT, AND NUMBER OF FIRMS IN THE FORMAL MANUFACTURING SECTOR

Number of firms	1996	1997	1998	1999	2000	2001	2002	2003	Average
Public	139	127	131	126	118	115	121	122	
Private	406	491	516	511	517	552	688	693	
Total	623	703	725	743	739	766	883	939	
Total number of firms growth	24	13	3	2	−1	4	15	6	8
Employment growth	1	2	1	0	1	−1	5	3	2
Output growth		4	16	6	−2	4	−2	−2	3
Export share of total sales (%)	7	7	9	4	5	10	9	10	8
Mean employment per firm	146.3	136.5	128.6	127.2	125.2	123.1	111.4	108.6	125.9
Median employment per firm	23	23	22	23	26	27	23	24	23.9

extensive policy reforms, including privatization, trade opening, and market deregulation.

Following the reforms, gross domestic product (GDP) per capita grew by about 1.5% per annum between 1994 and 2003 (see table 1). The contribution of the service sector to GDP in terms of value added increased from 35% to 47%, while the agricultural share shrunk from 55% to 43% in the same period. However, the share of the industrial sector remained almost constant, at around 11%.

The main data source of this study is 1996–2003 annual census data of manufacturing establishments collected by the Central Statistical Agency of Ethiopia (CSA 1996–2003). In this annual census only establishments with 10 or more employees are surveyed.[8] Table 2 gives summary statistics on output, employment, and number of firms by ownership of this formal manufacturing sector.[9] This sector has shown rapid growth in terms of number of firms with an annual average of about 8% between 1996 and 2003. The increase in the number of firms is due to the high entry rate in the private sector that came to account for about 85% of the population of firms in 2003.

[8] This means that small firms are underrepresented, which might introduce some bias into the analysis. We will, however, test the sensitivity of our results to the size limitation.

[9] In this analysis, establishment and firm are synonymous since most of the firms constitute a single plant.

The share of the private sector in terms of production and employment reached 38% and 42%, respectively, in 2003. The public sector is still the dominant employer, though this is a large increase of the private sector when it is compared to its share in 1989, with only 4% and 8%, respectively, of production and employment.

However, the manufacturing sector has performed poorly in terms of output, employment generation, and entry into the global market (see table 2). The growth rate of production and employment of the manufacturing sector between 1996 and 2003 was only 3% and 2%, respectively. This shows that the employment growth in the formal manufacturing sector is less than the population growth of the country. The sector is dominated by small firms, and the size distribution remained skewed with average employment at 126 and the median at 24. The share of exports to total manufacturing sales (1996 and 2003) was only 8% and showed no significant change in the last decade. The poor performance of the sector should be a great concern for policy makers given the widespread belief that economic transformation depends on the growth of the manufacturing sector.

The original data consisted of 6,121 firm/year observations. However, mainly due to quite a significant number of multiple entrants and exiting firms that account for about 7% of all firms, we deleted 579 observations and were left with 5,542 firm/year observations. Although firm size could be measured in terms of sales, or of value added or fixed assets, it is here defined in terms of the number of employees (i.e., the sum of permanent and temporary workers), unless otherwise stated.

B. Pattern of Firm Growth and Exit Rates

Which types of firms in Ethiopian manufacturing are more likely to grow/decline, survive, and exit? To address this question we calculated average growth and exit rates by size/age category. The growth of a firm is defined as the logarithmic difference of employment in 2 consecutive years.[10] Age is measured by the number of years since the firm's establishment. Exit or death refers to firms that disappeared from the data before the end of the sample period, and the exit rate is defined as the ratio of firms that exited in year t to the total number of firms in year $t-1$. Survivor firms are firms that continued to operate for the rest of the sample period, whether they were new entrants or had survived from before the sample period.

Table 3 presents firm growth and exit rates by size/age category. To calculate

[10] This means that growth rate can only be calculated for firms in the data set for at least 2 consecutive years, which reduces the number of observations for analysis.

TABLE 3

FIRM GROWTH AND EXIT RATES BY SIZE AND AGE CATEGORIES, 1996–2003

	Age Group					
Size Group	1–5	6–12	13–29	30–59	60+	Total
A. Mean employment growth rate, all firms:						
1. 10–19	8.68	5.33	2.64	3.48	−(1)	6.02
	(449)	(271)	(158)	(41)		(920)
2. 20–49	5.20	−2.24	−1.05	3.31	−(1)	1.71
	(146)	(82)	(80)	(34)		(343)
3. 50–99	−2.87	−10.27	1.52	−1.21	−(1)	−2.24
	(62)	(21)	(34)	(19)		(137)
4. 100–249	−.39	−.72	−4.50	−2.30	3.51	−2.09
	(23)	(17)	(34)	(31)	(5)	(110)
5. 250+	−1.37	−.72	−2.73	−3.68	−1.88	−2.80
	(16)	(7)	(20)	(73)	(17)	(133)
Total	5.11	.67	−.03	−1.1	−.53	1.72
	(696)	(398)	(326)	(198)	(25)	(1,643)
B. Mean employment growth rate, only survivor firms:						
1. 10–19	11.08	6.87	2.61	4.78	−(1)	7.47
	(183)	(100)	(51)	(23)		(357)
2. 20–49	7.85	1.39	.59	4.07	−(0)	4.20
	(85)	(40)	(50)	(26)		(201)
3. 50–99	−1.94	−4.04	3.10	.15	−(1)	−.44
	(40)	(15)	(18)	(13)		(87)
4. 100–249	.36	−1.00	−2.88	−1.66	3.51	−1.27
	(15)	(12)	(26)	(27)	(5)	(85)
5. 250+	−.32	−.72	−2.73	−3.68	−1.88	−2.71
	(11)	(6)	(19)	(70)	(17)	(123)
Total	6.86	2.50	.55	−.8	−.53	2.69
	(334)	(173)	(164)	(159)	(23)	(853)
C. Firm exit rate:						
1. 10–19	59.24	63.10	67.72	43.90	.00	61.20
2. 20–49	41.78	51.22	37.50	23.53	100	41.40
3. 50–99	35.48	28.57	47.06	31.58	.00	36.50
4. 100–249	34.78	29.41	23.53	12.90	.00	22.73
5. 250+	31.25	14.29	5.00	4.11	.00	7.52
Total	52.01	56.53	49.69	19.70	8.00	48.08

Note. The figures in parentheses in the upper two panels represent the number of firms in each size/age category. The figures not in parentheses are percentages, whereby the first two panels give the average firm growth rate, and the last panel gives the exit rate at each size/age category. For definitions of surviving and exiting firms and growth rates, see sec. 3A.

the growth and exit rates by size/age category, we take account of the unbalanced panel nature of our data, which consist of firms surviving throughout the sample period, exiting firms, and new entrants. A firm's first appearance in the data set is taken as a base year for its size and age category following Dunne et al. (1989). Each firm is classified in one of the five size/age categories according to its initial size/age, that is, size/age in year t ($t = 1996, 1997, \ldots, 2002$), and the growth rate of employment of each firm in its life period in the sample is calculated based on successive growth of size by year (i.e., from period t to $t + 1$, $t + 1$ to $t + 2$, etc.). Then we take the average of all

the firms' growth of employment in the given size category by year. The year-on-year growth rate is in turn averaged by size and age class for the entire sample period. The growth rate in each size/age class therefore represents the average rate of net employment generation by firms in the given size/age category.

The overall rate of employment growth is positive, with a 1.7% and a 2.6% annual average for all firms and only surviving firms, respectively. Table 3, panel A, gives the mean employment growth rate of all firms. The most dynamic firms in terms of growth are the small firms in the first two size classes and the young firms in the first age class. The average growth rates for the large firms and the old firms in the last three categories are negative. Thus, the growth rate declines with size (for a given age) and with age (for a given size) but not monotonically.

Table 3, panel B, gives the growth rates of only surviving firms. The growth pattern of the surviving firms is broadly similar to that of all firms. The best performers are the small firms in the first two size classes and the first two age classes (i.e., young survivors). This supports the previous result that firm growth declines with size (for a given age) and with age (for a given size) but not monotonically. Hence, the growth pattern by size/age category provides evidence that growth is systematically related to size and age. The hypothesis that growth is a stochastic process as implied by Gibrat's law is not supported.

We have also presented exit rates by size/age category in table 3, panel C. Exit rates decline monotonically with size and age. Smaller and younger firms fail more often than larger and older firms. This means that size and age are systematically correlated not only with growth but also with survival of firms. The smaller and the younger firms grow faster, but their survival rate is lower than that of the larger and the older firms.

C. Mobility of Firms: Matrix of Size Distribution

To investigate the ability of surviving firms to move within different size categories, we computed the mobility of firms across five size categories. Given the size category in the initial period, we calculated the percentage of surviving firms that transit into other size classes at the end of the period. Table 4 presents the matrix of size transition for 8-year and 5-year intervals.

Table 4, panel A, reports the mobility of firms in the 8-year period for the only 286 firms that survived the full sample period from 1996 to 2003. A significant number of small- and medium-sized firms "graduated" into their next higher size classes. About 33% of the first size class (10–19), 17% of the second size class (20–49), and 21% of the third size class (50–99) moved up to the next higher size class. About 10% of the firms in the medium-size

TABLE 4
TRANSITION MATRIX OF FIRMS BY SIZE CATEGORY

Size Beginning of the Sample Period	Size at the End of the Sample Period					
	10–19	20–49	50–99	100–249	250+	Total
A. Transition of size by employment, 1996–2003:						
1. 10–19	42	23	4	1	0	70
	(.60)	(.33)	(.06)	(.01)	(.00)	
2. 20–49	17	33	11	3	0	64
	(.27)	(.52)	(.17)	(.05)	(.00)	
3. 50–99	0	8	12	6	3	29
	(.00)	(.28)	(.41)	(.21)	(.10)	
4. 100–249	0	1	5	37	5	48
	(.00)	(.02)	(.10)	(.77)	(.10)	
5: 250+	0	2	1	12	60	75
	(.00)	(.03)	(.01)	(.16)	(.80)	
Total	59	67	33	59	68	286
B. Transition of size by employment, 1996–2001:						
1. 10–19	50	23	5	0	0	78
	(.64)	(.29)	(.06)	(.00)	(.00)	
2. 20–49	14	51	8	1	0	74
	(.19)	(.69)	(.11)	(.01)	(.00)	
3. 50–99	1	4	16	8	2	31
	(.03)	(.13)	(.52)	(.26)	(.06)	
4. 100–249	0	1	4	42	2	49
	(.00)	(.02)	(.08)	(.86)	(.04)	
5. 250+	0	1	3	5	66	75
	(.00)	(.01)	(.04)	(.07)	(.88)	
Total	65	80	36	56	70	307
C. Transition of size by employment, 1998–2003:						
1. 10–19	63	21	1	0	0	85
	(.74)	(.25)	(.01)	(.00)	(.00)	
2. 20–49	16	76	13	2	0	107
	(.15)	(.71)	(.12)	(.02)	(.00)	
3. 50–99	0	13	28	8	1	50
	(.00)	(.26)	(.56)	(.16)	(.02	
4. 100–249	0	1	4	51	5	61
	(.00)	(.02)	(.07)	(.84)	(.08)	
5. 250+	0	0	3	6	68	77
	(.00)	(.00)	(.04)	(.08)	(.88)	
Total	79	111	49	67	74	380

Note. The numbers in parentheses represent the ratio of firms that started in the size class of the row and reached the size class of the column at the end of the given period, while the numbers not in parentheses give the number of firms that belong to the given size category.

class (50–99) entered into the very-large-size class (250+), while none of the small firms in the first two size classes were able to jump into the 250+ size class in the 8-year period.

A large downsizing is observed, particularly among the medium-sized firms. For example, about 27% and 28% of the firms in the second and third size classes, respectively, moved down to the next lower size class from 1996 to

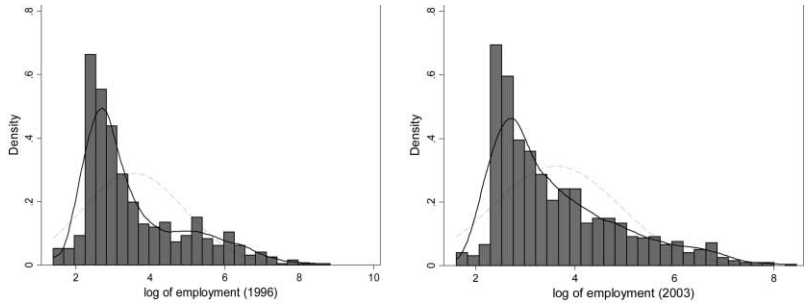

Figure 1

2003. Movements in both directions, scaling up and downsizing, are pronounced in these two size classes.[11] The general pattern of mobility in the 5-year intervals, reported in table 4, panels B and C, is broadly similar to the full sample period pattern discussed above.

Overall, the mobility across size classes is limited, with about 64% (184 firms) of the 286 survivor firms remaining in the same size class from 1996 to 2003. When we consider the 5-year transitions, the percentage of firms that stayed in the same size class rose to 73% and 75% for the periods 1996–2001 and 1998–2003, respectively. This is what one would expect given the difference in time intervals. Our results are consistent with Van Biesebroeck (2005), who analyzed size matrices for manufacturing in nine African countries: about three-quarters and two-thirds of firms remained in their initial size category for intervals of 4 and 8 years, respectively.

D. Testing for Log Normality of Size Distribution

In this subsection we present the formal analysis of firms' size distribution. The log-normality assumption in size, as implied by Gibrat's law, is equivalent to an assumption of normality on the log of size. We therefore rely on testing the log of employment to find whether the size distribution is log normal. If the log employment distribution deviates from normal, it is considered to be evidence against Gibrat's law (i.e., the observed size distribution is generated by a stochastic growth process).

Figure 1 shows the histogram on the distribution of log employment for the selected years 1996 and 2003, along with a kernel density function and

[11] This has to be accepted with some caution, because the mobility in the lower and upper ends of the size classes could be underestimated. The 250+ size class covers a wide range of sizes, and these firms cannot move up due to the size group arrangement. Neither can we see the downward movement in the lower size class with 10–19 employees due to the cutoff point at 10 employees in our data, which means that movement to a lower class implies exit.

the normal distribution plot for comparison. The long dashed line and the unbroken line represent the normal and the kernel density curves, respectively. As we can see in the figure, the log size distribution is far from normal. It is highly peaked and skewed with a long right tail and a large spike between 10 and 25 employees. We have also tested the normality assumption using numerical methods such as skewness, kurtosis, and the Shapiro-Francia normality tests by year (the results are not reported here for brevity).[12] All tests reject the normality assumption of log employment (i.e., the lognormal distribution of employment is rejected). The fact that the observed size distribution is far from lognormal is not consistent with the hypothesis that the firms' size is a result of a stochastic growth process. However, the test of lognormality of size distribution only provides indirect evidence that smaller firms grow faster than large firms. This requires direct tests between growth and size, which is the task of the next sections.

IV. The Econometric Framework and Empirical Results

A. The Growth Model and Statistical Issues

We now turn to directly testing the relation between growth and firm attributes, using econometric models. Following Evans (1987a), the firm growth-size/age relationship can be stated as

$$(\ln S_t - \ln S_{t-1}) = \ln G(S_{t-1}, A_{t-1}, X_{t-1}) + u_t, \tag{1a}$$

where S_t, A_t, and X_t denote firm size, age, and other firm attributes, respectively, and u_t is the disturbance term assumed to be normally distributed with mean zero and possibly a nonconstant variance.

Allowing for second-order expansion and considering the panel aspect of the data for firm i in year t, equation (1a) yields[13]

$$\begin{aligned} \ln S_{it} - \ln S_{it-1} = {} & a_0 + a_1 \ln S_{it-1} + a_2(\ln S_{it-1})^2 + a_3 \ln A_{it-1} \\ & + a_4(\ln A_{it-1})^2 + a_5(\ln S_{it-1} \times \ln A_{it-1}) \\ & + \sum_{j=1}^{k} b_j X_{it-1} + u_{it}. \end{aligned} \tag{1b}$$

[12] Unlike to the Shapiro-Wilk test for normality, the Shapiro-Francia test can accommodate a large number of observations (up to 5,000). A Shapiro-Francia statistic different from one implies divergence from normality. If the distribution is normal then the skewness and kurtosis are equal to zero and three, respectively. Skewness greater than zero shows right-skewed distribution, and kurtosis less than three implies that the distribution has thicker tails.

[13] Evans (1987a) proposed that it is better to start with higher-order expansion and then drop if insignificant, since there is little guidance for specifying a priori the functional form.

The partial derivatives with respect to size ($g_S = \partial \ln G/\partial \ln S$) and age ($g_A = \partial \ln G/\partial \ln A$) allow testing alternative theories of firm growth, where $g_S = 0$ implies no dependence of growth on size and evidence for Gibrat's law, and $g_A < 0$ supports the learning model prediction (Evans 1987a, 1987b).[14]

Size is measured in terms of employment and growth of size as the logarithmic difference of employment in consecutive years, unless otherwise mentioned. Age is measured by the number of years since establishment. The other firm attributes (X_{it}) included in the model are productivity, capital intensity, ownership, and location. Productivity is included to examine the passive learning model prediction that more efficient firms grow/survive while the less efficient ones contract/exit. The productivity variable in this model is labor productivity measured by output per employee. The output is corrected for price movements using an output price deflator at the two-digit industrial classification level, and labor is the sum of permanent and temporary workers.

Capital intensity is measured by the capital to labor ratio and is expected to capture firms' access to a wide range of resources, for example, access to capital. Location takes the value of one if the firm is located in Addis Ababa and surrounding towns (Debre Zeit, Nazirath, Burayu, and Sebeta) and zero otherwise. It is expected to capture differences among firms in access to better infrastructure and larger markets for skilled labor, raw materials, and outputs. The dummy variable "private" is defined as one if privately owned and zero otherwise. The expectation is that firms with high capital intensity that are privately owned and located in and around the capital city (as a large market area) will grow faster than their counterparts.

Several statistical issues arise in estimating equation (1b). The most serious statistical problem in such a model is the effect of sample censoring due to exit. Failures are common among small firms. Given that exit here is defined as those firms that disappeared from the data set, firms might exit due to a reduction in size to fewer than 10 workers, switching business, a shift into informality, or actually a shutdown. Small firms with slow or negative growth are more likely to exit than large firms. Thus, the proportional rate of growth conditional on survival will be small for large firms, and the growth of small firms will be biased upward. Ignoring this problem will result in a downward bias in the estimates of the relationship between firm growth and size. There are two popular methods to address this problem, the sample selection (Heckit)

[14] The elasticity of ending-period size to previous period size can be calculated as $E_S = \partial \ln S_{t+1}/\partial \ln S_t = 1 + g_S$, and elasticity of ending-period size to previous period age as $E_A = \partial \ln S_{t+1}/\partial \ln A_t = g_A$.

model following Hall (1987) and Evans (1987a, 1987b) and the grouping method following Dunne et al. (1989).

The Heckit model is mathematically elegant, but there are some problems in applying it. First, it relies on the distributional assumptions that the latent variable is normal, which is inappropriate. Second, separating sample selection, heteroskedasticity, and nonlinearity effects of the explanatory variables is difficult in this approach. Without imposing ultimately arbitrary restrictions on the functional form or including regressors in the survival equation that are not included in the growth equation, there is no way around this difficulty (Evans 1987b). We therefore address the sample selection problem relying on the Dunne et al. (1989) approach, since this could help us avoid the difficulties that arise from Heckit models (e.g., distributional assumptions and intercorrelation between sample censoring, heteroskedasticity, and nonlinearity).

We estimated two separate growth models using OLS: one for only surviving firms and the other for all firms, including exiting firms in their preexit period.[15] The latter could help tackle the bias that arises from excluding exiting firms in growth estimations. This bias is more for small firms. However, given that the small firms not only grow fast but also have a higher exit probability, exit should be explicitly considered as a -100% growth rate in the growth estimation. The relevant policy question is whether the growth rates of the smaller/new firms are large enough to compensate for their attrition rates (Dunne et al. 1989). For this reason we estimate a third growth model that explicitly considers exit as a -100% growth rate. Since no other variable is observed after exit, we use the values of other covariates (e.g., size, age, and productivity) of the preexit year. Then we apply OLS to estimate the growth rates on size, age, and other covariates for this extended data. Since the cutoff point in the survey is at 10 employees, the firms that reduce their size to fewer than 10 workers are treated as having exited, which is more likely among small firms than large firms. This is a strong assumption, but if we still find an inverse relation between growth and size, this can be taken as strong evidence against Gibrat's law.

The other major statistical concern is the phenomenon of regression to the mean arising from transitory fluctuations in size or transitory measurement errors in observed size. In order to address this problem we provide a separate estimation that relates average growth to mean size taking the yearly average of each firm size following the suggestion by Davis et al. (1996). This will

[15] Our approach differs from that of Dunne et al. (1989), particularly in relation to the definition of size/age. In their regression they use dummy variables that represent certain size/age classes rather than continuous variables.

be compared with results from an estimation of the growth model that relates current growth to current size, in order to examine the effect of transitory fluctuations in the growth-size relationship.

Most reported empirical firm growth models are criticized for their reliance on data sets that exclude micro and small firms. The concern is that the growth-size results might be sensitive to changes in the coverage of the data in terms of firm size. This is a concern in our data as well, since it does not cover firms with fewer than 10 workers. Thus, we test the robustness of our results by increasing the cutoff point from 10 to 20 workers, that is, by dropping firms with fewer than 20 workers from the estimation. We further examine the robustness of the growth-size relation using value added as alternative measure of size.

B. Empirical Results

This section discusses the empirical results of the firm growth model estimated using OLS on the pooled data. Table 5 reports the estimation and test results for six different specifications that include restricted and alternative versions of the basic model. The first three columns provide estimation results for surviving firms only, for all firms including exiting firms in their preexit period, and for all firms while considering exit as a growth rate of -100%, respectively. The fourth column reports results for a reduced sample that includes only firms with 20 and more workers. The fifth column gives mean growth and size/age results, and the last column introduces value added as alternative measure of size. In all estimations we control for industry (17 industries at the two-digit level) and year variations, but these are not reported here for brevity. The standard errors reported are heteroskedasticity consistent using the White (1982) method.

Smaller Firms Grow Faster

In all models size has a negative sign at the first level and a positive sign at the second order, and all are highly significant. The F-test for the null hypothesis that all second order size/age terms are jointly zero is significantly rejected in all models. The interaction term is positive but insignificant. A negative coefficient of the first term and a positive coefficient of the squared term for size imply that the relationship between growth and size is convex. This means that firm size affects growth negatively, but the negative effect diminishes with size and eventually turns positive.

When we compare the magnitude of the size coefficients among the different specifications, the first column (for only surviving firms) and the second columns (for all firms) are more or less identical. The maximum difference in

TABLE 5

OLS RESULTS OF THE GROWTH MODEL

	Current Employment Growth				Mean Employment Growth	Current Value Added Growth
Dependent Variable (Sample)	Surviving Firms Only (1)	All Firms (2)	All Firms with Exit = −100% (3)	Firms with > 20 Workers (4)	All Firms (5)	All Firms (6)
$\ln(S)_{t-1}$	−.386***	−.380***	−.255***	−.259***	−.443***	−.929***
	[.055]	[.046]	[.049]	[.041]	[.133]	[.074]
$\ln(A)_{t-1}$	−.168***	−.148***	−.155***	−.071*	−.116*	−.194*
	[.039]	[.034]	[.040]	[.038]	[.068]	[.106]
$\ln(S)^2_{t-1}$	.032***	.032***	.022***	.020***	.049***	.04***
	[.007]	[.006]	[.006]	[.004]	[.018]	[.004]
$\ln(A)^2_{t-1}$	.040***	.039***	.043***	.025***	.046***	.069***
	[.008]	[.007]	[.009]	[.007]	[.017]	[.021]
$\ln(S)_{t-1}\ln(A)_{t-1}$	−.003	−.005	−.005	−.007	−.023	−.007
	[.008]	[.007]	[.008]	[.007]	[.020]	[.068]
$(Y/L)_{t-1}$	.040***	.039***	.046***	.043***	.022**	.049**
	[.007]	[.006]	[.007]	[.006]	[.010]	[.022]
$(K/L)_{t-1}$	.023***	.021***	.023***	.014***	.020**	.067***
	[.005]	[.004]	[.005]	[.004]	[.009]	[.009]
Private	−.124***	−.134***	−.133***	−.089***	−.101*	−.498***
	[.033]	[.030]	[.031]	[.022]	[.064]	[.068]
Location	.042**	.038***	.037**	.031	.053**	.025
	[.019]	[.016]	[.019]	[.019]	[.026]	[.047]
Constant	.579***	.539***	.165*	.24*	.690***	3.97***
	[.126]	[.108]	[.127]	[.13]	[.229]	[.36]
N	3,087	3,814	4,162	2,460	1,049	3,254
R^2	.13	.12	.08	.086		.187
F-test (S2 = A2 = SA = 0)	$F(3, 3055)$ = 50.14***	$F(3, 3782)$ = 56.09***	$F(3, 4130)$ = 27.43***	$F(3, 2428)$ = 9.3***	$F(3, 1023)$ = 10.81***	$F(3, 3223)$ = 36.2***

Note. Year and industry dummies are included in all estimations. Note also that the numbers in brackets represent heteroskedasticity-robust standard errors.
* Represents the 10% level of significance.
** Represents the 5% level of significance.
*** Represents the 1% level of significance.

the respective coefficients does not exceed 0.03 percentage points. This means that the inclusion of exiting firms in their preexit period in the estimation does not alter the inverse growth-size relation. The size coefficient of the third column that considers exit as a −100% growth rate is slightly lower (in absolute value) compared to the first two columns, but the basic growth-size relation remains unaffected. The fact that this negative relation is not affected by our explicit consideration of the growth rate of exiting firms as −100% growth rate in the exit period suggests that the inverse relationship between growth and size is not a result of sample censoring. This is consistent with the previous studies that reported no evidence of sample selection bias using the Heckit model (Hall 1987; Evans 1987a, 1987b; Dunne and Hughes 1994, among others).[16] Hence, our data provide strong evidence that smaller firms grow faster than larger firms, which is contrary to Gibrat's law.

To test the robustness of our result we reduce the sample size by excluding the firms in size category 10–19 employees (see col. 4). All the coefficients are similar to those of the full sample models. The coefficient of size is negative and practically identical with the estimation results of the full sample that considers exit as a −100% growth rate. Hence, the inverse relation between growth and size is robust irrespective of the change in firm size coverage. This could be taken as indirect evidence that the inverse growth-size relation is not biased as a result of the exclusion of firms with fewer than 10 workers. In other words, the negative relation might hold even if we had been able to include also the firms that employ fewer than 10 people.

Examining whether the negative growth-size relationships found in the current size regression above holds when we estimate mean growth on mean size is also important given the concern for transitory fluctuation or measurement errors in size. Column 5 reports the OLS estimation that addresses the mean regression problem following the suggestion by Davis et al. (1996). The size coefficient is still negative and in fact higher in magnitude (in terms of absolute amount). Hence, the previous finding that smaller firms grow faster than larger firms is not affected by the transitory fluctuations or measurement errors in size.[17] Column 6 gives the estimation results using value added as

[16] We have also estimated the selection model using the Heckit framework (not reported here). We found that controlling for sample selection bias in this framework does not affect the relationship between growth and size/age.

[17] We have also estimated another specification that simultaneously corrects the censoring bias and spurious correlation, i.e., assigning a −100% growth rate to exiting firms in their exit period and averaging all the variables including size and growth over the years. The results are not reported here for brevity, but they are more or less the same as in the basic models and particularly in cols. 3 and 4 in table 5. This means that the growth and size/age relation is not affected by controlling for both concerns simultaneously.

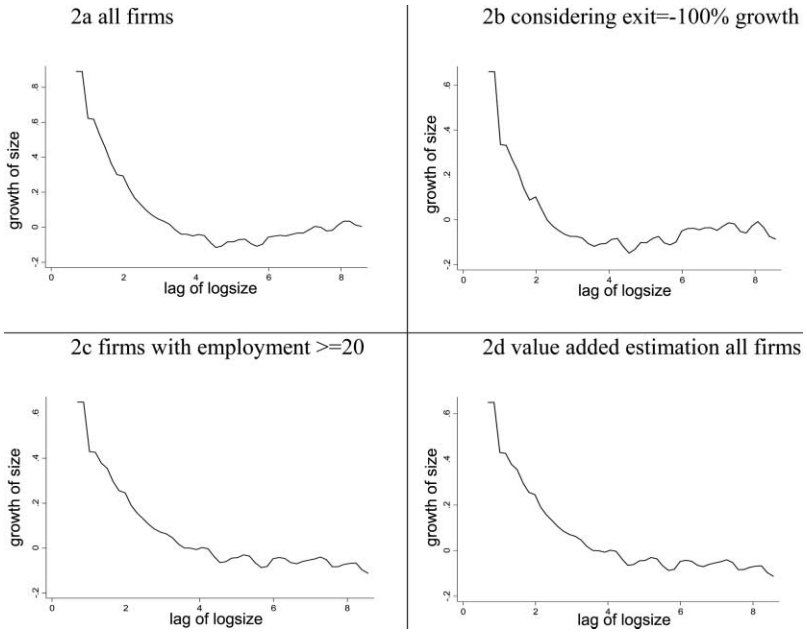

Figure 2

alternative measure of size. The value-added growth estimation provides broadly consistent results with the employment growth model. When we look at the size coefficient, the coefficient is again negative and high in absolute amount, providing even stronger evidence that smaller firms grow faster than larger firms.

In order to characterize the relationship between growth and size and to make tractable a comparison across the different specifications, we calculated the partial derivatives of size at different points: mean, median, 25th percentile, and 75th percentile (not reported here for brevity). The partial derivative of size at these four points is found to be negative for all models, except for some magnitude differences. This shows that firm growth decreases with size for the majority of the sample.[18] However, by focusing on the averages, as we do for the mean, median, and certain percentiles, the intermediate values might be overlooked. Thus, we present graphically the predicted growth and size relation in figure 2*a–d* to summarize the growth-size relationship. The figure

[18] The turning point at which the negative effect of size on growth turns positive (based on col. 2) is a size of 420 employees for a given mean age. We have calculated the percentage of observations that have a positive or negative sign of the partial derivative of size, taking as a reference the point where the negative slope turns positive. The signs of the partial derivatives of the growth function with respect to size were negative for about 92% of observations. This shows that firm growth decreases with firm size for more than 92% of the sample.

represents the predicted growth-size relationships derived from four specifications (i.e., cols. 2, 3, 4, and 6 in table 5, respectively). As we can observe from the figure, growth and size are inversely related for firms at least until they employ around 400 workers (i.e., log employment = 6) and the relations seem to be flat or slightly positive (depending on the model) beyond this size category. This confirms the previous findings that smaller firms grow faster than larger firms, and this is robust to sample selection, regression to the mean, changing the sample size, and value added as alternative measure of size.

Younger Firms Grow Faster

In all six models in table 5 age has a negative sign at the first level and a positive sign at the second order, and all are significant. The first level coefficient of age ranges between −0.07 and −0.19, and the second order between 0.025 and 0.069, depending on the model. A negative coefficient of the first term and a positive coefficient of the squared term for age imply that the relationship between growth and age is convex. This means that firm age affects growth negatively, but the negative effect diminishes with age. We have calculated the partial derivative of age at the mean, median, and the 25th and 75th percentiles. In all models the partial derivative of age is only negative at the 25th percentile, while the mean, median, and 75th percentiles show positive relations. The turning point at which the negative effect of size on growth turns positive (based on col. 2) is an age of 8.7 years for a given mean size.[19] This means that growth decreases with age for firms 9 years and younger, whereas growth increases with age for older firms. Hence, irrespective of the model the negative relation between growth and age predicted by the learning process affects only firms at the early stages of their life cycle (up to age 9).[20]

Figure 3*a–d* presents the predicted growth and age relation graphically based on four different specifications (i.e., cols. 2, 3, 4, and 6 in table 5, respectively). All models provide a kind of U-shaped relation between growth and age. Growth and age are inversely related only in the first few years after entry and stay constant for most of the age group until it starts to have a positive relation beyond age 50. This relation is not affected by sample selection, regression to the mean, changing the sample size, and value added as an alternative measure of size. This supports the previous findings that the

[19] Given the turning point of age at which the negative relation turns positive, we calculated the percentage of observations with negative and positive partial derivatives of age. The partial derivatives of the growth function with respect to age were negative for about 55% of observations based on the model in col. 2.

[20] Evans (1987a) found that firm growth decreases with age for younger firms but is roughly independent of age for older firms in U.S. manufacturing.

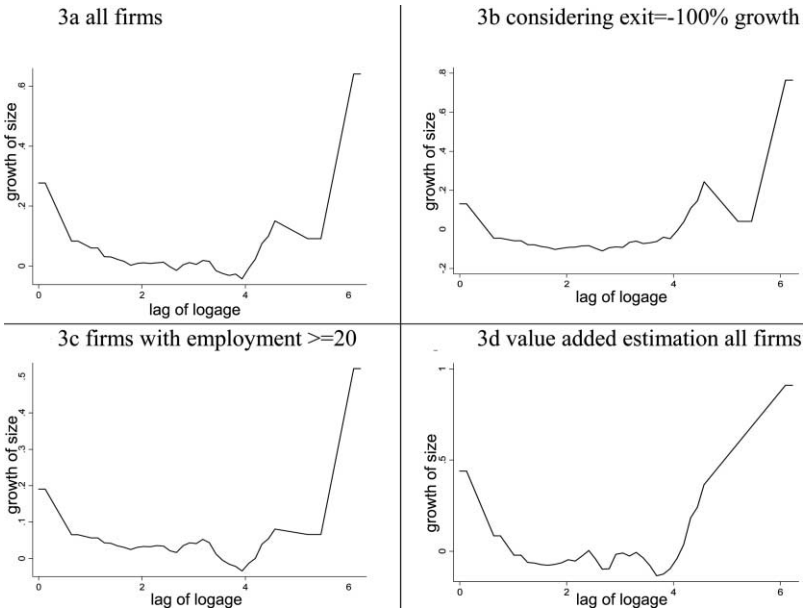

Figure 3

inverse relation between growth and age predicted by the learning model affects only firms at the early stages of their life cycle. Entrepreneurs learn about their relative efficiency over time following their entry, and thus growth is highest during this early period of learning as indicated by the Jovanovic model.

More Productive Firms Grow Faster

All the results reported in table 5 include productivity, capital intensity, ownership, and location as additional explanatory variables. Labor productivity is positively related to firm growth and significant in all models. The magnitude of the coefficient ranges from 0.02 to 0.05. This gives evidence that firms with higher labor productivity grow faster than firms with lower productivity. This means that the most productive firms are more likely to grow fast, which is consistent with the Jovanovic (1982) passive learning model arguing that firms get to know their true efficiency levels after entry through competition and experience, and then adjust their sizes accordingly. It also gives evidence of market selection, a process in which resources are reallocated from less productive to more productive firms through growth differentials.[21]

[21] Shiferaw (forthcoming) has used the same data to investigate market selection and finds that resources are reallocated toward more productive firms through a process of entry, exit, and survival

Capital intensity takes a positive and significant coefficient in all models, ranging between 0.014 and 0.067. This means that firms with higher capital-labor ratios grow faster than those with smaller capital-labor ratios, possibly indicating a difference in access to capital. Firms located in Addis Ababa and surrounding towns have also shown significantly faster growth than those located elsewhere, suggesting that better access to infrastructure and larger markets for inputs and outputs boost firm growth. Surprisingly, we found that public firms grow faster than private firms. This might indicate that they are less constrained in terms of access to capital and other resources than private firms.

V. Firm Growth and Unobserved Heterogeneity: Panel Data Analysis

Most previous studies testing Gibrat's law are based on cross-sectional regressions of average growth in size over a period of time on initial size. This specification is sometimes augmented by other covariates such as age, efficiency, and other firm characteristics. These models implicitly assume that all sources of heterogeneity among firms are fully reflected in the observed variables. However, the size growth relationship can also be affected by other unobserved firm-specific factors, such as background and skills of entrepreneurs, workers' skills, access to credit, and the environment in which the firms interact. These unobserved factors might be correlated with the initial size and other covariates in the model, so that the growth differentials among firms might be driven by these unobserved advantages. As a result, the effects of the explanatory variables, including initial size, will be overestimated. Failing to control the unobserved heterogeneity will provide biased coefficients. Mata (1994), Das (1995), Liu, Tsou, and Hammitt (1999), and Goddard, Wilson, and Blandon (2002) found unobserved firm-specific effects correlated with other covariates and applied panel data techniques to control for unobserved heterogeneity based on annual firm growth.

The panel nature of our data allows us to control for unobserved heterogeneity across firms.

$$\Delta \ln S_{it} = \ln S_{it} - \ln S_{it-1} = \beta \ln S_{it-1} + \gamma X_{it-1} + \mu_i + u_{it}, \qquad (2a)$$

where μ_i captures unobserved and time-constant firm-specific effects, X_{it} other covariates, and u_{it} the pure error term; β determines the relationship between growth and size. Gibrat's law predicts that $\beta = 0$, while a correlation between size and growth ($\beta \neq 0$) contradicts the law.

driven by efficiency differences. He also finds that international competition increased the rate of industry rationalization.

Equation (2a) can be reformulated to a dynamic setting as follows:[22]

$$\ln S_{it} = \beta^* \ln S_{it-1} + \gamma x_{it-1} + \mu_i + u_{it}, \tag{2b}$$

where $\beta^* = (\beta + 1)$. Gibrat's law is supported if the null $\beta^* = 1$ is not rejected, whereas $\beta^* < 1$ implies that smaller firms grow faster than larger firms.

The introduction of a lagged dependent variable creates some problems in the estimation. Since the current size (S_{it}) is a function of firm-specific factors (μ_i), then lagged size (S_{it-1}) is also a function of (μ_i). Therefore, the lagged size on the right-hand side of the equation is correlated with the error term. Estimating equation (2b) by OLS will produce biased and inconsistent estimates of β^*. If we assume that the unobserved effect is fixed over time, the FE approach wipes out the omitted variable bias. However, using FE may introduce a new type of endogeneity in the presence of a lagged dependent variable as an explanatory variable. This is because the within transformation ($S_{it-1} - \bar{S}_{i.-1}$), where

$$\bar{S}_{i.-1} = \sum_{t=2}^{T} S_{it-1}/(T-1),$$

is still correlated with ($u_{it} - \bar{u}_i$), and thus the FE approach is biased and its consistency depends on T being large.[23]

The first difference method is also inappropriate, since it relies on the strong assumption that the explanatory variables should be sequentially exogenous. Instrument variable models that correct for endogeneity are necessary in this context. Arellano and Bond (1991) proposed a GMM estimation method where the lagged levels of the explanatory and the dependent variable are used as an instrument for the first differenced equation. Given the poor performance of the GMM models, particularly in the presence of high serial correlation, Blundell and Bond (1998) proposed a system GMM that uses lagged first differences of the explanatory variables and the dependent variable as instruments in addition to the levels instruments.

We use the system GMM estimation (SYS-GMM) developed by Blundell and Bond (1998) to estimate equation (2b), but for comparison we have also

[22] This transformation could help reduce the measurement error that arises from the growth estimation.

[23] In general the FE approach relies on an extreme assumption that the explanatory variables are strictly exogenous. When the strictly exogenous assumption fails, particularly in the presence of high persistence in $\{x_{it}\}$, the FE estimator is biased.

estimated the fixed effect model.[24] Table 6 reports the estimation results. The first three columns provide estimation results on the full data set, while the next three columns are for the reduced sample size at which the cutoff point increases from 10 to 20 employees to test the robustness our results.

In choosing the proper instruments for SYS-GMM estimation, we estimated and compared various specifications based on different sets of instruments such as first lags and second lags with and without earlier lags. According to the Sargan-Hansen test of overidentification, the validity of instruments with only first lag and first and earlier lags are decisively rejected (not reported here). Instruments with $t-2$ and $t-2$ and earlier lags passed the Hansen test of overidentification. We then further tested the validity of additional instruments (i.e., the validity of instruments $t-2$ and earlier lags in contrast to only $t-2$ lag) using the Sargan-Difference test. The calculated Sargan-Difference statistics are below the critical value even at the 10% level of significance in all specifications, which means that we are not able to reject the validity of earlier lags as additional instruments.[25] Moreover, the SYS-GMM with $t-2$ and earlier lags provide reasonable estimates of the parameters of interest. Thus, table 6 reports only our preferred model; the SYS-GMM estimates that use $t-2$ and earlier lags as a set of instruments.

In all specifications size takes a value less than one. The appropriate test of Gibrat's law in the level equation, that the lag size is equal to one, is strongly rejected (see the last row in table 6). This is evidence that supports the previous finding that small firms grow faster than larger firms. Age is found to be negative and significant, suggesting young firms grow faster than older firms. Productivity is positively related to current size, confirming that the more productive firms grow faster, that is, the process of market selection through differential growth. Location in Addis Ababa and surrounding areas is also found to be a growth advantage. Unlike our pooled OLS results, capital intensity and ownership variables are not significant though they have the same sign.

[24] The dummy variables such as ownership, location, and industry are excluded from the FE since these are time-constant variables. Age is also excluded, because a variable that varies by one unit each year does not make sense in a panel, particularly when year dummies are included.

[25] The SYS-GMM results that use only $t-2$ instruments are not reported here to save space. The calculated Sargan-Difference test between col. 2 (which uses a set of instruments $t-2$ and earlier lags) and a model with a set of instruments only $t-2$ gives $\chi^2(24) = 28.26$. This is less than the critical value (i.e., 42.97, 39.36, and 33.19 at the 1%, 5%, and 10% levels, respectively), thus the validity of the additional instrumental variables is not rejected. The calculated Sargan-Difference test between col. 3 (which uses a set of instruments $t-2$ and earlier lags) and the model with a set of instruments only $t-2$ is $\chi^2(24) = 30.3$, and this is again less than the critical value, thus the validity of the additional instrumental variables is not rejected.

TABLE 6

FE AND SYS-GMM RESULTS OF THE LEVEL ESTIMATIONS

Dependent Variable Current Log Employment Level	All Firms			Firms with > 20 Workers		
	FE	SYS-GMM	SYS-GMM	FE	SYS-GMM	SYS-GMM
$\ln(S)_{t-1}$	.11* (.061)	.447* (.248)	.247 (.285)	.339 (.091)	.586*** (.23)	.403 (.328)
$\ln(A)_{t-1}$			−.312** (.133)			−.128 (.268)
$\ln(S)^2_{t-1}$	.017*** (.007)	.053** (.027)	.052** (.027)	−.005 (.01)	.039* (.024)	.052 (.029)
$\ln(A)^2_{t-1}$			.04 (.035)			.004 (.039)
$\ln(S)_{t-1}\ln(A)_{t-1}$			.055 (.0497)			.041 (.06)
$(Y/L)_{t-1}$	.023*** (.007)	.090*** (.037)	.082** (.04)	.027 (.009)	.126*** (.041)	.11*** (.039)
$(K/L)_{t-1}$	.02*** (.008)	.002 (.022)	−.004 (.021)	.017 (.008)	−.015 (.018)	−.004 (.023)
Private			−.053 (.20)			−.087 (.166)
Location			.266* (.15)			.154 (.15)
Constant	2.75*** (.167)	.33 (.553)	1.23* (.774)	2.628 (.252)	−.139 (.589)	.475 (1.16)
N	3,817	3,817	3,814	2,461	2,461	2,460
Tests:						
Sargan-Hansen test		76.89 [.451]	69.20 [.538]		73.88 [.548]	70.28 [.502]
m1		−7.83 [.00]	−7.19 [.00]		−6.79 [.00]	−6.36 [.00]
m2		2.26 [.024]	1.99 [.047]		1.89 [.058]	1.78 [.076]
$\ln(S)_{t-1} = 1$[a]	213.88 [.00]	4.97 [.026]	7.01 [.008]	52.58 [.00]	3.23 [.07]	3.31 [.069]

Note. The standard errors are robust finite samples corrected on two-step estimates derived from Windmeijer (2000). The Sargan-Hansen test of the overidentifying restriction is a minimized value of the two-step GMM criterion function and is robust to heteroskedasticity or autocorrelation, and the null is that the instruments are valid. The serial correlation test is also reported as m1 and m2 to represent the AR(1) and the AR(2) tests, respectively, under the null of no serial correlation. The *p*-values of these different tests are reported in brackets. The set of instruments in the respective columns constitute all RHS variables. FE = fixed effects; SYS-GMM = system GMM estimation.

[a] In the level equation the Gibrat's law is supported if the null hypothesis that the coefficient of the lag size is equal to one (i.e., $\beta^* = 1$ in eq. [2b]) is not rejected. However, in all models the null is decisively rejected (see the bottom row).

* Represents the 10% level of significance.

** Represents the 5% level of significance.

*** Represents the 1% level of significance.

When we take the sample of firms with 20 and more employees, some of the variables continue to be significant, while others turn out to be insignificant. The size coefficient is still less than one and significant at the 10% level in the SYS-GMM estimation. Labor productivity is also positive and significant in both the SYS-GMM estimations. However, age, capital intensity, location, and ownership are not significant though they take the expected signs.

To sum up this section, all models provide strong evidence that small firms grow faster than larger firms. Hence, the previous finding that there is an inverse relation between growth and size is robust after controlling for the effect of unobserved heterogeneity and the problem of endogeneity in the growth regression. Productivity affects growth positively and significantly, confirming our previous finding that the more productive firms grow faster.

VI. Conclusions

We have used annual census–based firm-level data of Ethiopian manufacturing from 1996 to 2003 to investigate the relationship between firm growth and firm attributes such as size, age, and productivity. Firm size is defined in terms of employment. In the descriptive section we examined the pattern of firm growth and the exit rate by age and size category, mobility of firms across size class, and the size distribution of firms. We then estimated and compared various econometric models. Unlike most previous studies in SSA, we explicitly addressed the ongoing statistical concerns in firm growth models such as sample censoring, regression to the mean, and unobserved firm heterogeneity. The following main conclusions can be drawn from our analysis.

First, the mobility of firms across the size distribution in Ethiopian manufacturing is generally limited, and the size distribution remains skewed. The mobility of firms across size categories shows that about two-thirds and three-fourths of the firms stay in their initial size class for 8 years and 5 years, respectively. However, a significant number of small- and medium-size firms make a transition into the next larger size class, and a large downsizing is observed among the medium-sized firms in the 1996–2003 period. As in most other developing countries, the sector is dominated by small firms mainly due to a low rate of urbanization, poor infrastructure, and a cumbersome regulatory environment.

Second, firm growth decreases with size, and this is not affected by the transitory fluctuations or measurement errors in size, corrections for sample censoring, or by controlling for unobserved firm heterogeneity. Hence, our data provide strong evidence that smaller firms grow faster than larger firms, contrary to Gibrat's law. Neither is the negative relation between growth and size affected by our setting of the growth rate of exiting firms to be −100%

in the exit period. This suggests not only that smaller firms have faster rates of employment growth than larger firms but also that the growth rates of the smaller firms are large enough to compensate for their attrition rates. The inverse relation between growth and size not only holds but improves when we use value added as alternative definition of size. Thus, policies aimed at encouraging small firms might have a significant effect not only on employment but also on output growth.

Third, the relation between growth and age is mixed. Firm growth increases with age for older firms but decreases with age for younger firms in their early stages. This means that the learning hypothesis that predicts a negative relation between age and growth affects only the younger firms in the early stages of their life cycles. The justification for the negative relation between growth and age is that entrepreneurs learn about their relative efficiency over time; thus, growth is highest during this learning period, as indicated by Jovanovic's model. However, the relation between growth and age could take another form after some time, since age might then capture effects that are more likely for older firms than for younger firms, such as improved reputation and network advantages.

Fourth, labor productivity affects firm growth positively, implying that more productive firms grow faster. This is consistent with the passive learning model prediction that firms get to know their true efficiency levels after entry through experience and adjust their size accordingly. It also provides evidence of market selection, where a reallocation of resources from less efficient to more efficient firms takes place through growth differentials.

Fifth, firm growth is also affected by other factors. Firms with higher capital intensity grow faster than those with lower capital intensity. Firms located in and around Addis Ababa (the capital city) also grow faster, mainly capturing access to better infrastructure and larger markets for inputs and outputs. We also found that publicly owned firms grow faster than private firms. This might point to differences in access to finance and other network advantages for public firms. In other words, the private sector in Ethiopia might have less access to these resources, and therefore their growth may be constrained.

Based on the availability of census and longer panel data set for the Ethiopian manufacturing sector, this article fills an empirical gap in the literature on firm growth in SSA. However, it is not without limitations. The data set excludes firms with fewer than 10 employees, and therefore the majority of manufacturing firms in Ethiopia are excluded from the analysis. As a result, the scope of the findings is limited to the formal sector, and it remains to be seen if it applies to the micro firms. Thus, future work is required to address this issue.

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