ECONOMIC STUDIES

DEPARTMENT OF ECONOMICS
SCHOOL OF BUSINESS, ECONOMICS AND LAW
GÖTEBORG UNIVERSITY
152

ESSAYS ON FIRM TURNOVER, GROWTH, AND INVESTMENT BEHAVIOR IN ETHIOPIAN MANUFACTURING

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ISBN 91-85169-11-0
ISBN 978-91-85169-11-5
ISSN 1651-4289 print
ISSN 1651-4297 online

To my wife Letensea and our children Senait and Brook

Abstracts

This thesis analyses the dynamics and investment behavior of Ethiopian manufacturing firms in post-reform period using establishment level industrial census panel data from 1996 to 2003. Three related topics such as firm turnover and productivity differentials, determinants of firm growth, and the effect of adjustment cost and irreversibility on firm investment decisions are investigated empirically.

Essay I provides empirical evidence on firm turnover and productivity differentials in Ethiopian manufacturing using firm-level census data from 1996 to 2003 and tries to address the following research questions. Are the forces of market selection at work in Africa? How successful are markets in these economies to sort out firms on efficiency basis following the sequence of reforms to liberalize and particularly to transform some of the previous command economies to market oriented ones? What is the pattern of entry and exit in the manufacturing sector and how does it affect industry productivity growth? This is the first attempt to analyze firm turnover and productivity differentials using industrial census data in sub-Saharan Africa. The Ethiopian manufacturing sector exhibits high firm turnover rate that declines with size. Exit is particularly high among new entrants; 60 percent exit within the first three years in business. Our study consistently shows a significant difference in productivity across different groups of firms, which is reflected in turnover pattern where the less productive exit while firms with better productivity survive. We also found higher aggregate productivity growth over the sample period, mainly driven by firm turnover.

Essay II examines the relationships between firm growth and firm size, age, and labor productivity, using annual census based panel data on Ethiopian manufacturing firms. Unlike most previous studies in sub-Saharan Africa, this study explicitly addresses the ongoing statistical concerns in the firm growth models such as sample censoring, regression to the mean, and unobserved heterogeneity. Overall, our empirical results indicate that firm growth decreases with size. This relation is not affected by fluctuations or measurement error in size and by controlling unobserved heterogeneity. It is also robust after correcting for sample censoring and explicitly considering the growth rate of exit firms to be -100 percent in the exit period. This suggests not only that smaller firms have faster rates of employment growth than larger firms, but also

that growth rates of the smaller firms are large enough to compensate for their attrition rates. The negative relation between growth and age predicted by the learning process is found to impact only younger firms at the early stage of their life cycles. Labor productivity affects firm growth positively. This is consistent with the passive learning model prediction and provides evidence of a market selection process through growth differential. Capital intensity, location in the capital city, and public ownership also affect firm growth positively.

Essay III investigates the effect of irreversibility and non-convexities in adjustment costs on firm investment decisions based on 1996-2002 firm level data from the Ethiopian manufacturing. It relies on a rich census based panel data set that gives the advantage of disaggregating investment into different types of fixed assets. We document evidence of a large percentage of inaction intermitted with lumpy investment, which is consistent with irreversibility and fixed costs but not with the standard convex adjustment costs. The inaction is higher and investment lumpier for small firms. We complement the descriptive analysis with two econometric methods: a capital imbalance approach and machine replacement model. With the capital imbalance approach we estimate the investment response of firms to their capital imbalance using a non-parametric Nadaraya-Watson kernel smoothing method. With the machinery replacement approach using a proportional hazard model that takes unobserved heterogeneity into account, we estimate the probability of an investment spike conditional on the length of the interval from last investment spike.

Acknowledgments

During the course of my PhD program, there were many people who were instrumental in helping me. Without their guidance, help and patience, I would have never been able to accomplish the work of this thesis. I would like to take this opportunity to acknowledge some of them.

First of all, I would like to express my deepest gratitude to my Advisor, Arne Bigsten, who has been very supportive throughout my stay in the graduate program. He provided me a direction and valuable and timely advices. I benefited a lot from his broad understanding of African economies. I am particularly, grateful to him for allowing me the latitude to pursue my interest within the general framework of industrial development. It was his, persistence, understanding and kindness that I am able to complete my thesis timely. I am also highly indebted to Måns Söderbom, particularly whose expertise in the African manufacturing to be very valuable. As co-advisor and discussant on my final seminar, his detail comments and guidance on all essays improve the quality of the thesis significantly. I must also acknowledge Lennart Hjalmarsson and Ola Olsson for their continuous interest and support on my thesis.

I want also to thank my fellow colleagues and friends in the department of economics for providing stimulating and fun place to work: Carl Mellström, Matilda Orth, Anders Boman, Gustav Hansson, Peter Ljunggren, Simon Olehäll, Karin Gullon, Andreea Mitrut, Florin Maican, Constantin Belu, Daniel Zerfu, Precious Zikhali, Innocent Kabenga, Wisdom Akpalu, Mintiwab Bezabih, Marcela Ibanez, Miguel Quiroga, Qin Ping, Sven Tengstam, Jigen Wei, Anna Widerberg, Jorge Garcia, Rahimaisa Abdula, Mahmud Yesuf, and Abebe Shimeles. I am also very grateful to seminar participants in the department and those provide me support in one way or another in the last four years includes: Lennart Flood, Olof Johansson-Stenman, Dick Durevall, Per-Åke Andersson, Gunnar Köhlin, Jinghai Zheng, and Anders Ekbom. I also wish to thank Eva-Lena Neth Johansson, Eva Jonason, and Elizabeth Földi for their tireless help in adminsitrative matters.

I also wish to express my gratitude to Dr. Gebrehiwot Ageba. He was the first person who suggests applying for Phd program in Göteborg University. I also appreciate the continuous support of Ethiopian Development Research Institute (EDRI).

Ato Neway Gebre-ab as a director of the institute and Ato Mezgebe Mihretu as administrator, among others deserve special thanks for their support.

At last but not least, I wish to thank my family and friends for encouraging me to pursue this program and supporting me at every step along the way. Particularly, I must acknowledge my wife Letensea and our children Senait and Brook, who have never lost faith in this long-term project. This thesis is dedicated to them.

Despite the numerous comments and suggestions I received, errors and ommisions are my own responsibility.

Mulu Gebreeyesus

Göteborg, February 2006

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Introduction and Overview of the Thesis

1. General Introduction

This thesis examines the post-reform period performance and behavior of firms in the Ethiopian manufacturing sector in three self-contained essays. Specifically, it deals with issues related to firm turnover, growth, and investment behavior, using establishment level annual census data for Ethiopian manufacturing from 1996 to 2003.[1] It tries to address the following broad questions. Are market selection forces at work following the reforms to liberalize the economy? How does growth vary across firms and which type of firms grow fast? Why do firms invest so little despite the presence of high profit rates in comparison to the developed world?

The absence of well functioning markets has been considered to be one cause of the poor performance of the manufacturing sector in sub-Saharan Africa (SSA hereafter) and among developing countries at large. "Getting the price right" was regarded as an essential prerequisite for sustainable industrial growth. Hence, most of these countries have adopted structural adjustment programs to liberalize and open their economies. A number of countries, including Ethiopia, have also made a transition from a command economy to a market oriented one.

Despite these reforms, the manufacturing sector in most SSA countries has virtually stagnated in the last two decades. In 2002 the share of manufacturing value added to GDP in SSA was only about 15 percent, the lowest in the world (WDI, 2004). The sector is dominated by small firms and can still not meaningfully enter into the export market. The investment rate among manufacturing firms is also low with a median investment rate equal to zero, despite high profit rates in comparison to other regions, and this is not generally explained by financial constraints (Gunning and Mengistae, 2001).

These are indeed important research issues. Most previous empirical works in SSA have been based on survey data, mainly from the RPED surveys. While these studies helped improve our understanding of the manufacturing sector in the region, they were unable to capture some aspects of the dynamics of the sector (e.g. issues related to firm

[1] All calendar years in this thesis are in Gregorian calendar (GC).

entry, exit, and investment behavior), mainly due to the nature of the survey data. Thus, the empirical gap in SSA remains substantial.

This thesis helps fill this gap by providing empirical evidence on firm dynamics and investment behavior from the Ethiopian manufacturing. In light of this contribution, two important features of the country in focus (Ethiopia) are worth noting. First, it is one of the many countries that transformed from a command economy to a market oriented one, and therefore has the character of a transition economy and the timing of the study represents a period of continuous structural adjustment. Second, it is a sub-Saharan African country with a small industrial base.[2]

The novelty of this study is its reliance on establishment level industrial census panel data. The main data source is the annually collected data for the 1996-2003 period on all manufacturing establishments with 10 or more employees by the Ethiopian Central Statistical Authority (CSA). The data set contains information on employment, production, a variety of costs, fixed assets, investment, and other firm characteristics. The obvious advantage of this data set is that it enables us to investigate firm performance and behavior in different dimensions, such as entry and exit, contraction or expansion, capital investment by different asset types, and productivity.

2. Background of the Study

In the era of the military government (1975-91), the private sector in Ethiopian manufacturing was stifled by the confiscation of industrial establishments of nationals and foreigners, a capital ceiling imposed on the private sector of half a million Ethiopian Birr, restrictions on the supply of foreign exchange, price controls, and discriminatory credit policies.[3] Consequently, most of the manufacturing firms were state owned and protected from domestic and foreign competition. The output, factor, and credit markets were heavily regulated. Hence, entry and competition and as a result productivity improvements were dampened.

After about two decades of centralized economic policy a new government took power in 1991, and has since undertaken extensive policy reforms to transform the

[2] Further background of the study is discussed in the next section.

[3] The exchange rate was fixed in the 1975-91 period, and according to the official exchange rate of the Birr versus the US Dollar at that time (2.08 Birr/1USD), the ceiling on private investment was roughly about a quarter of a million USD.

economy into a market oriented one. The reforms include privatization, trade opening, and market deregulation, all expected to promote competition. The foreign exchange market has been liberalized starting with a massive devaluation of over 200 percent in October 1992, and an auction system has been introduced. Most price controls and restrictions on private investment have been lifted. The maximum tariff rate has been reduced from 240 percent to 35 percent. A large number of public establishments have been privatized. At the same time, autonomy to operate on purely commercial basis has been given to the management of the remaining public establishments. The financial market has also been liberalized by making lending rates market determined.

Table 1 shows the performance indicators of the Ethiopian economy in the post-reform period. GDP per capita grew at an annual average rate of 2.6 percent from 1994 to 2002. The service sector share of GDP in terms of value added increased from 35 percent to about 48 percent, while the agricultural share shrank from 55 to 40 percent during the same period. However, the industrial sector share of GDP remained almost constant, at around 11 percent.

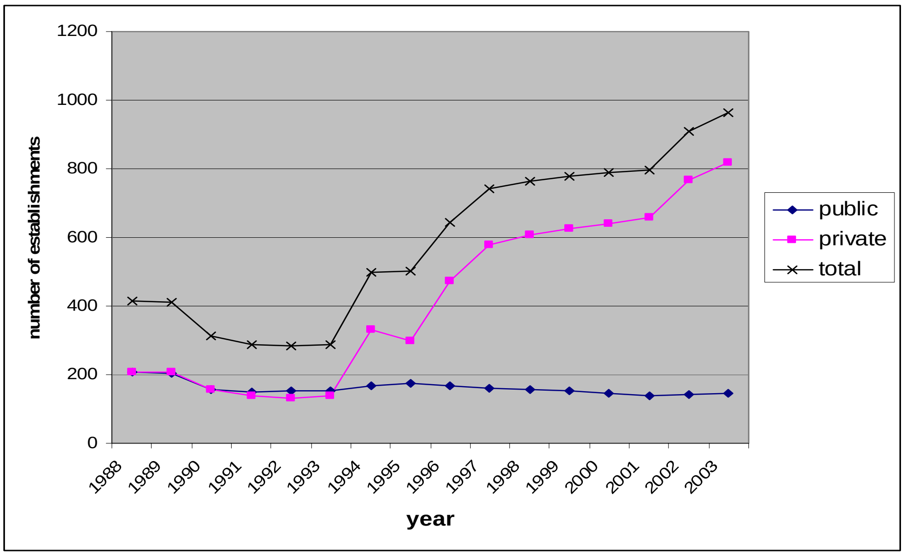
Table 1 Share of GDP and growth rates of sectors, Ethiopia 1994 – 2003.

	1994	1995	1996	1997	1998	1999	2000	2001	2002
GDP growth	3	6	11	5	-2	6	6	9	3
GDP per capita growth	0	3	8	3	-4	4	3	6	1
Industry, value added (% of GDP)	10	9	9	10	11	11	10	11	12
Industry value added growth (%)	7	8	5	3	2	9	2	5	6
Services value added (% of GDP)	35	34	33	37	44	43	43	45	48
Services value added growth (%)	8	9	7	7	10	8	9	5	5
Agriculture value added (% of GDP)	55	56	58	53	45	46	47	44	40
Agriculture value added growth (%)	-4	3	15	3	-11	4	2	11	-3

Source: World Development Indicators (WDI) 2004

The formal manufacturing sector with 10 or more workers has shown a rapid growth in terms of number of firms (see Figure 1). In the period of heightened civil war and change of government (1989-92), the number of firms declined by about a quarter. This trend was reversed in 1993 and the number of firms almost tripled from 1993 to 2003. The rise in the number of firms was due to the high entry rate in the private sector, which accounted for about 85 percent of the firm population in 2003. The share of the private sector in terms of production and employment reached 38 and 42 percent respectively in 2003. While the public sector is still the dominant employer, this is a large increase compared to the share of the private sector in 1989 of only 4 percent and 8 percent of production and employment, respectively (CSA, 1990).

Figure 1 Trend of the number of establishments in Ethiopian manufacturing



Source: Central Statistical Authority of Ethiopia (CSA)

However, the manufacturing sector performed poorly in terms of output, employment generation, and entry into the global market (see Table 2). The production and employment growth rates of the manufacturing sector from 1996 to 2003 were only 3 percent and 2 percent, respectively. The sector is dominated by small firms. On average, the small firms with 10 to 19 workers account for about 42 percent of the total number of firms. The share of export of manufacturing products to total merchandise export for the 1995-2002 period was about 10 percent, and the share of exports to total manufacturing sales from 1996 to 2003 was only 8 percent. Neither ratio showed any significant change in the last decade.

Table 2 Manufacturing output, employment, and number of establishments

	1996	1997	1998	1999	2000	2001	2002	2003	average
# of establishments	623	703	725	743	739	766	883	939	
Growth in number of firms	0.24	0.13	0.03	0.02	-0.01	0.04	0.15	0.06	0.08
Growth of employment	0.01	0.02	0.01	0.00	0.01	-0.01	0.05	0.03	0.02
Growth of production		0.04	0.16	0.06	-0.02	0.04	-0.02	-0.02	0.03
Exports ratio to total sales	0.07	0.07	0.09	0.04	0.05	0.10	0.09	0.10	0.08
Manufacture exports ratio to merchandise exports[a]	..	0.10	0.07	0.07	0.10	0.13	0.14		0.10
Size by employees (mean)	146.3	136.5	128.6	127.2	125.2	123.1	111.4	108.6	125.9
Size by employees (median)	23	23	22	23	26	27	23	24	23.9
Percentage of firms with less than 20 workers	44.5	42.7	44.4	42.9	40.7	36.9	43.7	42.4	42.3
Percentage of firms with 100 or more workers	24.2	22.0	21.9	23.0	21.9	22.7	20.2	20.6	22.1

[a] Source: WDI (2004), but for all the rest Central Statistical Authority of Ethiopia (CSA)

3. Summaries

The first essay provides empirical evidence on firm turnover and productivity differentials in the Ethiopian manufacturing sector using firm-level industrial census data from 1996 to 2003. This study mainly tries to address how successful the market forces are at sorting out firms on an efficiency basis, and the effect of firm turnover on aggregate productivity growth. Examining the market selection process and its benefits is pertinent given the sequence of reforms aimed at promoting competition and productivity growth. As far as I know, this is the first attempt to analyze firm turnover and productivity differentials using industrial census data in sub-Saharan Africa.

I examined the pattern of entry and exit rates and compared average productivity of continuing, exiting, and entering firms using two measures of productivity: TFP constructed from system GMM models, and labor productivity. I also estimated a probit model of the exit decision to examine if productivity helps predict exit after controlling other firm attributes. Finally, I investigated the effect of resource reallocation on productivity growth by decomposing productivity growth into within-firm, between-firm, and turnover effects, following Baily, Hulten, and Campbell (1992).

The study reveals a number of facts about firm dynamics in Ethiopian manufacturing. The sector exhibits a substantial annual firm turnover rate of about 22 percent over the period 1996 to 2003. The turnover rate is higher among smaller firms and decreases with size. Firm churning in Ethiopian manufacturing is large in comparison to industrial economies. This might be due to the dominance of light industries with low-start up capital and the transition nature of the economy from a command to a market oriented one. The exit rate among new entrants, particularly in the first three years, is found to be very high. More than 60 percent of new entrants exit within three years after their entry. This shows that the entering cohorts themselves undergo a shakedown period, and that market selection is even harsher for these new entrants.

The pattern of firm turnover partly reflects productivity differences across firms. On average, exiting firms are less productive than continuing and entering firms. Exiting firms also exhibit a downward productivity trend before exiting which is evidence of a “shadow of death” effect. Productivity levels also predict exit after controlling for other firm characteristics such as size, age, and capital intensity. This shows that as in most developed countries, markets in Ethiopia do not tolerate inefficient firms.

Contrary to the existing notion, public firms are on average found to be more productive than private firms. This could be explained by the nature of the privatization process and the immaturity of the private sector. The government tends to sell less profitable firms and retain those with better profitability, and most of the privatized firms undergo an adjustment period that may reduce their productivity in the short-run. However, the productivity differential could also reflect differences in access to resources such as finance and other network advantages in favor of public firms.

The manufacturing sector, as a whole, exhibits high productivity growth mainly driven by the turnover effect. The average productivity of entering firms in their first year is higher than that of exiting firms in their last year, implying that dying firms are replaced by new, and more productive firms. The contribution of incumbents to aggregate productivity growth is approximately zero. Studies in transition and new emerging economies have also reported a large contribution of the turnover effect on aggregate productivity growth, particularly where the firm churning is found to be high.

The second essay investigates the characteristics of fast growing firms, and particularly the relationships between growth and size, age, and labor productivity, using firm level data on the Ethiopian manufacturing sector from 1996 to 2003. This is important for countries that strive for industrialization and policies that aim at creating jobs.

Understanding the relationship between growth and size is of particular interest for countries like Ethiopia, given that most firms are small. Firm size is defined in terms of employment. Unlike most previous studies in sub-Saharan Africa, this study explicitly addresses the ongoing statistical concerns in firm growth models such as sample censoring, regression to the mean, and unobserved firm heterogeneity. The main findings can be summarized as follows.

First, the mobility of firms across the size distribution in Ethiopian manufacturing is limited. The sector is dominated by small firms and the size distribution remains skewed. This reveals the distinctive feature of firm size distribution in developing countries' manufacturing, mainly attributed to low urbanization, poor infrastructure, small domestic market, and poor regulatory environment.

Second, firm growth decreases with size, and this relation is robust after correcting for sample censoring and unobserved firm heterogeneity, and is not affected by the transitory fluctuations or measurement errors in size. This provides strong evidence that smaller firms grow faster than larger firms, which is contrary to Gibrat's law. The inverse relation between growth and size also holds with our explicit consideration of exit rate as -100 percent growth in the exit period, suggesting that the growth rate of small firms is large enough to compensate for their higher attrition rates. The implication is that small firms have an important role in the development process, and policies that aim at promoting small firms might have a significant growth effect.

Third, firm growth decreases with age for younger firms and increases with age roughly after age 10. This implies the learning hypothesis that predicts that a negative relation between age and growth affects only the younger firms in the early stages of their life cycles. The justification for this negative relation is that entrepreneurs learn about their efficiency relative to others over time; thus growth is highest during this learning period. However, the relation between growth and age could take another form after some time, since age might capture effects other than learning. In light of this, the positive relation between growth and age after 10 years might be due to reputation building and network advantages which are more likely for older firms than younger firms.

Fourth, firms with high labor productivity tend to grow faster. This provides evidence of market selection at where continuous reallocation of resources from less efficient to more efficient firms takes place through growth differential. Capital intensity, location in capital city, and public ownership also affect growth positively, mainly reflecting better access to various resources such as infrastructure, larger markets for inputs and outputs, and finance.

The third essay examines whether irreversibility and fixed cost of adjustment are important determinants of investment decisions in Ethiopian manufacturing using 1996-2002 firm level data. This study is motivated by the fact that investment in Ethiopian manufacturing firms is low with a median investment rate equal to zero, despite high profit rates. The descriptive analysis shows that the second-hand market for machinery and equipment is almost non-existent, implying that investment is essentially a sunk cost, i.e. irreversible. Episodes in which firms refrain from engaging in any investment activity are very high, accounting for 58 percent in an average year. This large inaction rate reflects the presence of fixed component of adjustment costs and that investment is largely irreversible. The importance of fixed costs is also supported by the evidence of lumpy but infrequent investments. This pattern of investment is consistent with theories of irreversibility under uncertainty, where firms remain liquid until the marginal return of capital exceeds a certain threshold level.

To formally infer the shape of the adjustment costs from the observed firm behavior, I applied two econometric methods. The first one is known as the capital imbalance approach, following Caballero and Engel (1994), and uses the non-parametric Nadaraya-Watson kernel smoothing method to examine how firms adjust their capital stock to deviations in their desired capital from their actual capital stock. I found a large flat portion (range of inaction) followed by a positive and non-linearly increasing portion of the adjustment cost curve. The large range of inaction shows a long period of zero investment, and is consistent with investment being largely irreversible. The non-linear relation on the other hand suggests that a certain threshold of capital imbalance is necessary to make investments which in turn results in bunching of investments in few periods, consistent with irreversibility and fixed adjustment costs.

Using the second method known as the machinery replacement model, I estimated a proportional hazard model with and without unobserved heterogeneity for discrete time following Cooper, Haltiwanger, and Powers (1999), to test if the probability of investment spikes conditional on the length of the last investment spike exhibits positive duration dependence. I found an upward sloping hazard, particularly for the disaggregated fixed assets, which is consistent with fixed adjustment costs. However, the test for the null that the hazard is flat can not be rejected, implying that the fixed effect prediction is weaker. For the aggregated investment the hazard is declining, consistent with the convex adjustment cost that might be a result of aggregation of heterogeneous capital.

4. Concluding Remarks and Policy Implications

This study reveals a massive reallocation of resources in Ethiopian manufacturing following the reform, with substantial firm entry, firm exit, failure of many new entrants, and expansion of the successful ones. Survival reflects productivity differentials across firms. Productivity also affects firm growth positively. This means that more productive firms grow faster and survive; therefore, resources are reallocated from less efficient to more efficient ones. As in many other developed countries, market selection forces are at work and the competitive pressure is relatively strong in Ethiopia. This process in turn helps improve aggregate productivity growth in the sector.

Size is found to have a significant effect on growth and survival of firms. The finding supports the stylized fact in developed countries that the growth prospect is higher for smaller firms, but that the probability of survival is higher for larger firms. This implies that small firms have a very important role to play in the development process and gives some justification for promotion of small firms. Other firm attributes that have been found to determine growth in other countries for example, age, location, ownership, and capital intensity are also affecting firm performance in Ethiopia, mainly reflecting differences in access to various types of resources.

Surprisingly, public firms are on average found to be more productive and grow faster than private firms. The notion that public firms are inefficient is therefore not supported by our data. This is partly explained by the nature of the privatization process and the short history of the private sector in Ethiopian manufacturing. However, it could also reflect differences in access to various aspects of resources, e.g. finance and network advantages favoring public firms. The private firms, mostly new and small, might have less access to these resources. This is indeed a concern, given the development strategy of the country that the success of the manufacturing sector and the economy at large will hinge upon the private sector development.

The paradox of low investment and high profit rates in Ethiopian manufacturing is partly explained by the presence of irreversibility and fixed adjustment costs. The absence of a second-hand market for machinery and equipment and a high frequency of zero episodes of investment in comparison to the industrialized economies are clear evidence of the adverse effect of irreversibility and uncertainty on investment in Ethiopia. The infrequent but lumpy investments documented also indicate the significance of irreversibility and fixed adjustment costs. Firms tend to respond slowly to avoid costly mistakes, despite favorable changes in fundamentals. This calls for policy intervention particularly in improving the investment climate, such as reducing policy uncertainty and institutional hurdles, improving the second-hand machinery and equipment market, and providing better infrastructures, since the effect of irreversibility and fixed costs is more pronounced when there are problems in these areas.

In general, the removal of market distortions in Ethiopia has produced some gains as indicated by the productivity growth in the manufacturing sector following the reforms. However, the sector is still dominated by small firms and its share in the economy remains stagnant. Firms invest less and can still not meaningfully enter the export market. This shows that the previous reform that largely aimed at “getting the price right” is not sufficient to spur sustainable growth given the existing structural rigidities in countries like Ethiopia. This study suggests that those micro-institutional factors such as, uncertainties, inadequate infrastructure, and other resource constraints are significant obstacles. The response of managers in a recent firm survey conducted for Ethiopian manufacturing supports this view.[4] The firms mentioned poor infrastructure and tax administration, lack of access to land and loans, bureaucratic hurdles, and an inefficient judiciary as major obstacles for doing business (World Bank and EDRI, 2003). This justifies the shift in emphasis from “getting the price right” to removing “critical resource” constraints, improving governance, and building investor confidence as policy priorities.

This study also suggests important areas for future research. Why is firm churning among new and young firms so high? Relating firm performance explicitly to trade

[4] The survey was conducted in 2002 by the World Bank in collaboration with the Ethiopian Development Research Institute (EDRI) on about 423 manufacturing firms.

opening, access to finance, public services, and transaction costs at large might enrich our understanding of the determinants of success in Africa manufacturing. The overall success of economic reform is expected to rely on private sector development. But our data indicates that private firms are on average less productive and grow slower than public firms. Investigating what particular obstacles are impeding the growth of private firms is therefore imperative. Irreversibility and fixed adjustment costs are found to be important determinants of the investment decision of firms. It would also be useful to assess how important the non-convexities are in understanding aggregate investment fluctuations.

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ESSAY I

FIRM TURNOVER AND PRODUCTIVITY DIFFERENTIALS IN ETHIOPIAN MANUFACTURING

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Abstract

Are the forces of market selection at work in Africa? How successful are markets in these economies in sorting out firms on an efficiency basis following the sequence of reforms to liberalize and particularly to transform some of the previous command economies to market oriented ones? What is the pattern of entry and exit in the manufacturing sector and how does it affect industry productivity growth? This study examines these issues using firm-level industrial census data from the Ethiopian manufacturing sector. It is the first attempt to analyze firm turnover and productivity differentials using industrial census data in sub-Saharan Africa. The Ethiopian manufacturing sector exhibits a high firm turnover rate that declines with size. Exit is particularly high among new entrants; 60 percent exit within the first three years in business. Our study consistently shows a significant difference in productivity across different groups of firms, which is reflected in a turnover pattern where the less productive exit while firms with better productivity survive. We also found higher aggregate productivity growth over the sample period, mainly driven by firm turnover.

Keywords: Entry and exit, productivity, manufacturing, Africa.

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1. Introduction

The absence of well functioning markets has been considered to be one cause of the poor performance of the manufacturing sector in sub-Saharan Africa and in developing countries at large. Consequently, liberalization and deregulation have been major ingredients of the reforms that have been taking place in these countries since the 1980s. A large number of countries including Ethiopia have also made a transition from a command economy to a market oriented one. The main premise is that excessive regulation and protection inhibit competition, and as a result inefficient firms survive and better firms are discouraged from entering into an industry. Competition therefore could improve productivity growth in an industry, where instead the more efficient enter and expand, while the less efficient shrink and exit.

Are the forces of market selection at work in African industries? How successful are markets in these economies in sorting out firms on efficiency grounds following the reforms? What is the pattern of entry and exit in the manufacturing sector and how does it affect industry productivity growth? What are the determinants of the decision to exit? The purpose of this study is to address these issues using firm level industrial census data on the Ethiopian manufacturing sector from 1996 to 2003.

Analysis of producer turnover and productivity differentials is a recently emerging literature. Jovanovic (1982) presented the first formal model on the relation between productivity differentials and firm turnover and growth. According to this model, firms update their prior expectations after entering as a result of experience, and become certain about their true “type”. Firms experiencing low true costs survive or/and expand, while firms with higher costs shrink or/and exit. The model also predicts that firm survival is positively related to firm size and age as these variables themselves are the results of previous market selection processes.

Hopenhayn (1992) discusses firm dynamics in a more elaborate way using a stochastic model. The model relies on the existence of a threshold level of productivity defining a point of equilibrium for entering as well as exiting an industry. In equilibrium, firms exit the industry when their state of productivity falls below the minimum productivity level ($x < x^*$). Hopenhayn explains particularly the effect of an increase in entry cost on the evolution of an industry. The higher the entry cost, the less the selection and the higher the expected lifetime of incumbents. A higher entry cost also reduces entry by raising the level of discounted profits needed to make entry profitable. This means that when entry costs are high, less productive firms survive and potential entrants are discouraged. The implication for productivity growth is that investments are made by less efficient firms, therefore productivity growth declines.

Entry cost might arise from policies and regulations that inhibit entry/expansion or exit/contraction. Tybout (2000) argues that business regulations are unusually dense and unpredictable in developing countries. Price controls, regulations on foreign trade, foreign currency rationing, poor tax administration and business licensing, policy instability, and general uncertainty could make the entry cost high and have similar consequences of limiting the market selection process.

There are different views about the relative productivity of new entrants and the incumbents. The vintage effect argument predicts higher productivity of young firms (i.e. due to their advantage of acquiring new technology) than old firms, and thus productivity declines with the age of the firm. However, the learning process consistent with most empirical findings predicts that entering firms are on average less productive than incumbents.

A higher firm turnover might reflect the existence of a market selection process, but it doesn't necessarily imply that only inefficient firms are driven out of the market. Particularly in developing countries, where shock smoothing instruments are lacking, sound firms might also be driven out. Therefore, it is useful to explore empirically whether exit is random or the result of a persistent productivity fall. The latter is known to be a "shadow of death" effect following Griliches and Regev (1995).

There is growing interest in studying firm dynamics in manufacturing industries following the theoretical work by Jovanovic (1982) and Hopehayn (1992). Baily, Huston and Campbell (1992) and Olley and Pakes (1996) for the US manufacturing sector, Griliches and Regev (1995) for Israel, Aw, Chen and Roberts (1997) for Taiwan, Chin-Hee Hahn (2000) for South Korea, Liu (1993) for Chile, and Liu and Tybout (1996) for Colombia and Chile, provide empirical evidence on the relation between producer turnover and productivity differentials. Recently, Bartelsman, Haltiwanger, and Scarpetta (2004) also presented evidence on firm turnover and productivity comparing the industrial and developing countries where the latter constitutes some Latin America countries and transition economies in Eastern Europe.

However, such studies are scant in sub-Saharan Africa (SSA hereafter) mainly due to a lack of industrial census data. Recently, Harding, Soderbom, and Teal (2004) examined exit (one of the dimensions of turnover) and productivity differences for three African countries based on survey data. Unfortunately, no sample survey can capture the producer turnover and its effect on industry productivity growth, thus the existing gap can only be bridged by industrial census (Gunning and Mengistae, 2001).

As far as our review, this study is the first attempt in SSA to analyze firm turnover and productivity differentials using industrial census data, and will help fill the existing gap. We use panel data for the eight year period from 1996 to 2003, covering all manufacturing establishments in Ethiopia with 10 or more employees. The Ethiopian manufacturing sector exhibits a high firm turnover rate that declines with size. Exit is particularly high among new entrants, of which more than 60 percent exit within the first three years in business. Our study consistently shows a significant difference in productivity across different groups of firms, which is reflected in a turnover pattern where the less productive exit while firms with better productivity survive. We also found higher aggregate productivity growth over the sample period, mainly driven by firm turnover.

The next section presents issues related to the data source and background. Section 3 provides the pattern of entry and exit. Section 4 discusses methodological issues in measuring productivity. Section 5 compares the average productivity differential among continuing, entering, and exiting firms. Section 6 examines the determinants of the exit decision. Section 7 presents the contribution of turnover on aggregate productivity growth, and the last section summarizes the findings.

2. Data Source and Construction of Relevant Variables

The main data source of this study is the annual census data for manufacturing establishments with 10 or more employees collected by the Ethiopian Central

Statistical Authority (CSA) from 1996 to 2003. The original data comprises 6,121 firm/year observations. Due to inconsistency in id-numbers and industrial classification, we deleted 9 observations and were left with 6,112 observations representing 1,764 firms. We also found a large number of firms entering and exiting multiple times. These account for about 7 percent of total firms. While they are kept in the analysis of the exit and entry pattern, they are excluded from the productivity analysis due to a problem in constructing a capital stock, although this exclusion might introduce some bias into our estimation.

We used industrial output deflators at the two-digit level of industrial classification to deflate nominal outputs. However, for raw materials we used a GDP deflator due to the absence of sectoral input deflators. For electricity we used the electricity deflator from official sources, while for oil we constructed a price deflator from the reported use of volume and value of oil in the data.

The original data provides beginning of the year capital, investments, sold assets if any, and end-year capital for each firm and year. However, for the sake of consistency we constructed new series of capital stock using the perpetual inventory method.[1] For each firm we took the beginning year capital (when it enters the data set) as a base and constructed capital stock sequentially by adding investments and subtracting sold assets and depreciation. We used different depreciation rates for different types of assets: 8 percent for machinery and equipment, 5 percent for buildings and 10 percent for vehicle and furniture and fixture. Then we derived a new capital stock series for use throughout the analysis, by taking the average of the beginning and the end year capital stock.

Labor is measured by the sum of permanent and temporary workers, the latter adjusted to year equivalent labor. However, to consider the quality difference in labor we constructed a labor quality index using the average wage differential between production workers, non-production workers, and seasonal workers. Thus, in this study labor input refers to the number of employees indexed to quality differences among these groups.

[1] The capital stock is calculated as $K_{it} = K_{it-1} + \frac{I_t}{p^t} - \delta K_{it-1} - sK_{it}$, where K_{it-1} denotes the beginning year capital, p^t investment deflator, δ depreciation rate, and sK_{it} sold assets in year t.

3. Pattern of Firm Entry and Exit

We grouped firms into three categories: continuing, entering, and exiting firms. Continuing firms are firms that stay in the data set throughout the sample period, i.e. from 1996 to 2003. Entry or birth refers to a firm that appears for the first time in the data set after the beginning of the study period, in our case after 1996. The entry rate (E_t/N_{t-1}) at year t is therefore defined as the ratio of the number of entering firms to the total number of firms operating in the previous year, where E_t denotes the number of firms observed in year (t) but not in year (t-1). Exit or death on the other hand refers to firms which disappeared from the data set before the sample period ended. Exit rate (X_t/N_{t-1}) is then defined as the ratio of firms that exited in year t to the total number of firms in the previous year, where X_t denotes the number of firms observed in year (t-1) but not in year (t). The turnover rate is then a simple average of the entry and exit rates.[2]

Table 1 gives the pattern of entry and exit rates in the Ethiopian manufacturing sector. On average about 25 percent of firms entered and about 19 percent of firms exited every year from 1996 to 2003. Firm entry largely out-paced firm exit making net entry positive. The average turnover rate in this period is about 22 percent. However, if we exclude the firms with multiple entrants, then the average turnover rate becomes 20 percent.

We separated the firms into four size-groups to investigate any size related effects on turnover rate. As we can see from Table 1, the turnover rate decreases with size. The average turnover rate across the years for the size category (10-19) is 33 percent. This rate is more than double that of the next two size classes (20-49 and 50-99) and more than five times that of the large firms (100 or more employees). This is clear evidence that most of the flux takes place among the very small firms that employ 10 to 19 workers.

[2] A firm entering the data base might be due to either expansion of employment to 10 or more persons or "green field" investment. At the same time the firm exit from the data could be due to either shutdown or contraction of employment to less than 10 persons. Our data does not identify whether the entry is due to "green field" investment or expansion or whether the exit is due to shutdown or contraction. The exit record from contraction might bias the exit rate, and this is expected to be particularly pronounced for small firms that employ a number of persons around the cut-off point, 10 employees.

Table 1 Firm entry and exit rates by size and year

	Entry rate (E_t/N_{t-1})					Exit rate (X_t/N_{t-1})					Turnover rate				
	Size category by number of employees				All firms	Size category by number of employees				All firms	Size category by number of employees				All firms
Year	10-19	19-49	50-99	>=100		10-19	19-49	50-99	>=100		10-19	19-49	50-99	>=100	
1997	0.44	0.34	0.38	0.07	0.32	0.29	0.16	0.15	0.06	0.20	0.37	0.25	0.26	0.06	0.26
1998	0.41	0.16	0.15	0.05	0.25	0.38	0.13	0.16	0.04	0.22	0.40	0.14	0.15	0.04	0.24
1999	0.23	0.13	0.11	0.09	0.19	0.32	0.07	0.05	0.03	0.17	0.27	0.10	0.08	0.06	0.18
2000	0.34	0.16	0.16	0.05	0.24	0.35	0.18	0.09	0.08	0.24	0.35	0.17	0.12	0.06	0.24
2001	0.22	0.15	0.12	0.04	0.19	0.25	0.10	0.06	0.03	0.15	0.23	0.13	0.09	0.04	0.17
2002	0.62	0.22	0.14	0.05	0.33	0.26	0.17	0.11	0.03	0.18	0.44	0.19	0.12	0.04	0.25
2003	0.25	0.10	0.14	0.06	0.21	0.22	0.08	0.09	0.03	0.14	0.24	0.09	0.12	0.04	0.18
Avg.	**0.36**	**0.18**	**0.17**	**0.06**	**0.25**	**0.30**	**0.13**	**0.10**	**0.04**	**0.19**	**0.33**	**0.15**	**0.14**	**0.05**	**0.22**

Notes: for definition of entry, exit, and turnover rate see Section 3.

Although the annual average turnover rate found in Ethiopian manufacturing is higher than in previous studies on industrialized countries and some Latin American countries (see Tybout, 2000, and Bartelsman et al., 2004), it is close to the rates reported by Aw et al. (1997) for Taiwanese manufacturing and by Hahn (2000) for Korean manufacturing based on five year intervals. The high turnover rates in these newly industrialized countries are partly explained by the rapid expansion of their manufacturing sectors (Tybout, 2000).

Bartelsman et al. (2004) documented high turnover rates and positive net entries also in the Eastern Europe transition economies in their comparison with industrial countries. They argued that this is due to the process of transition, whereby the new firms not only displace obsolete incumbents but also fill new markets which were nonexistent or poorly populated in the past. This is a plausible argument in the Ethiopian context, but we think there are also other possible explanations to the high turnover rate.

A large number of firms seem to have entered into the market in a short period of time following the elimination of the previous restrictions on private sector investment. However, at the same time there are other factors that might work in the opposite direction and make the exit rate high as well. The entering firms and incumbents are exposed to intense competition with each other and with the surge of imports as a result of trade liberalization. Moreover, in a highly uncertain environment there is also a high incentive to be flexible in terms of productive capacity, which increases the dominance of light manufacturing industries (with low start-up capital) in which the exit and entry costs are smaller (Tybout, 2000). The absence of shock smoothing instruments in developing countries such as Ethiopia might also aggravate the turnover rate.

How does the turnover affect the mix of firms and the reallocation of jobs and output in the manufacturing sector? To address this question we calculated the contribution of entrants and exit firms to the population of firms, total jobs, and output by entry/exit cohorts. Table 2a gives the entrant contributions by different cohorts of entry.[3] For example, in 2001 the ratio of entrants less than 3 years old and

[3] Table 2 will be clearer if we read it as follows. For example, the cell in the first row and first column in Table 2a could be interpreted as the number of firms that entered in three years (i.e. 1999 - 2001)

less than 5 years old to the total number of firms was 36 percent and 54 percent, respectively. The ratio of firms less than 5 years old in 2002 and 2003 was similar. This shows that more than half of the firms operating in these years were no more than 5 years old.

Table 2 Contribution of entering/exiting firms and lifetime of new entrants

2a. Contribution of entering firms (unit %)

year	Entering within 5 years									Entering over 5 years		
	1-3 years			4-5 years			Total =< 5 year					
	firm	job	output	firm	job	output	firm	job	output	firm	job	output
2001	36.3	15.0	14.5	17. 8	8.6	10.5	54.1	23.6	24.9	45.9	76.4	75.1
2002	43.5	14.2	8.7	12.6	9.2	14.8	55.9	23.4	23.5	44.1	76.6	76.5
2003	40.0	14.1	10. 7	13.1	10.2	12.0	53.1	24.3	22.7	46.9	75.7	77.3

2b. Contribution of exiting firms (unit %)

year	Dying within 5 years									Dying after 5 years		
	1-3 years			4-5 years			total =<5 years					
	firm	job	output	firm	job	output	firm	job	output	firm	job	output
1996	38.5	9.6	6.5	10.8	3.6	2.4	49.3	13.2	8.9	50.7	86.8	91.1
1997	42.1	11.4	9.0	8.1	2.99	1.5	50.2	14.4	10.6	49.8	85.6	89.5
1998	38.5	10.4	13.3	7.9	3.26	1.97	46.3	13. 7	15.3	53.7	86.3	84.7

2c. Lifetime of new entrants (unit %)

	Exit within 5 years									Survive beyond 5 years		
	1-3 year			4-5 year			total					
year	firm	job	output	firm	job	output	firm	job	output	firm	job	Output
1997	66.0	57.9	42.6	8.0	5.5	4.3	74.0	63.4	46.9	26.0	36.6	53.1
1998	64.5	37.5	27.9	7.7	13.8	7.4	72.2	51.3	35.3	27.8	48.7	64.7
1999	59.8	32.3	46.0									

The high entry rate affects not only the mix of firms but also the market share in terms of output and employment. The new firms less than three years old accounted for 15 percent of employment and those firms less than 5 years old accounted for 24

accounts for 36.3% of the total number of firms in 2001. The next column shows the percentage of total jobs created by these entrants in 2001. The other cells should be read in the same way.

percent of employment in 2001. The output contribution of these cohorts is 14 percent and 25 percent respectively for the same year. The employment and output shares of these cohorts were similar the following two years, 2002 and 2003.

Table 2b gives the percentage of firms that exited, and lost jobs and output due to this. The ratios of firms that closed within three years to the total number of firms in the years 1996, 1997 and 1998 were 38.5 percent, 42.1 percent and 38.5 percent, respectively. The proportion of firms that closed within five years was about one-half in 1996 and 1997, but was marginally lower in 1998. These firms accounted for between 13 and 14 percent of the total job destruction, and for between 9 and 15 percent of the output lost in the same years. The higher ratios of firm exits in comparison to the ratios for lost jobs and output suggest that the death rate is higher among small firms.

We next investigate exit rates among new entrants, which we designate as conditional exit, to shed light on the market selection process that sorts out successful and less efficient entrants. As we can see from Table 2c, the exit rate was much higher in the first three years after entry. For example, 66 percent of the firms that entered in 1997 exited within three years. The jobs and output lost in these three years were also significant: 57.9 and 42.6 percent of the total jobs and output created by the 1997 entrants.

The exit rate among new entrants is very high particularly in the first three years compared with the unconditional exit rate (see Table 2b). For instance, in 1998 the conditional exit rate (within three years) was higher (64.5 percent) than the unconditional exit rate (42.1 percent). However, the conditional exit rates in the 4th and 5th year after entry are similar to the unconditional rates. This provides evidence of higher infant mortality, since the death rate is highly concentrated to the early ages of life, one to three years. Our finding supports the view that new firms with different levels of efficiency learn and gain experience gradually, whereby in the process the efficient survive and the inefficient exit.[4] This is also consistent with other previous studies (for example Roberts and Tybout, 1996, and Bartelsman et al., 2004).

[4] One alternative view is the capital vintage effect that new firms acquiring better technology are more efficient than old firms, thus the probability of exit is higher among older firms.

4. Measuring Productivity and Methodological Issues

4.1 Methodological Issues

The choice of productivity measure is an important challenge given the existing diverse methodologies. The commonly used labor productivity (Y/L) overstates productivity when the capital-labor ratio rises without a change in underlying technology. The total factor productivity (TFP) takes account of multi-factors but entails various methodological concerns depending on the assumptions we are willing to make.

In calculating the TFP we start by specifying a production function.[5] Assuming a Cobb Douglas specification with four factors and transforming it to logarithmic form yields;

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_r r_{it} + \beta_m m_{it} + \eta_{it} + v_{it}, \qquad (4.1)$$

where y, k, l, r and m are output, capital, labor, raw material, and indirect industrial costs in log form respectively, η_{it} firm specific aspect of productivity which is known by the firm but not by the econometrician, and v_{it} a pure random error that is unknown to both the econometrician and the firm.

The total factor productivity is therefore derived from the deviation between the firms' actual production and predicted output as follows:

$$TFP_{it} = y_{it} - \beta_k k_{it} - \beta_l l_{it} - \beta_r r_{it} - \beta_m m_{it}, \qquad (4.2)$$

where the β's represent factor elasticity estimated from the production function.

However, the method that relies on the production function to construct TFP poses a concern on the consistency of the estimated coefficients, the common problems being simultaneity and selection biases.[6] The OLS is inconsistent in the existence of these biases. Different methods that control the unobserved effects have been developed with the availability of panel data. If we are willing to assume that the major source of simultaneity bias (the unobserved effects such as marginal ability, labor quality, etc.) is fixed over time, then the fixed effect can be eliminated

[5] The Divissa index that takes factor shares of inputs as weight in deriving TFP, without estimating econometrically, relies on strong assumptions such as that all markets are competitive, factors are paid their marginal productivity, and constant returns to scale among others.

[6] The simultaneity bias arises when the firms' knowledge of their own productivity levels affects their choice of inputs, thus the unobserved fixed effect is correlated with the observed inputs. The selection bias on the other hand arises because firm exit is not exogenous since smaller firms with less capital intensity are more likely to exit.

by introducing a separate intercept for every firm (known to be LSDV) or by using the "within transformation", thus the estimators from this estimation are consistent. Assuming that the unobserved effect is fixed in equation (4.1) gives:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_r r_{it} + \beta_m m_{it} + \eta_i + v_{it} \,. \tag{4.3}$$

Then the "within transformation" yields:

$$(y_{it} - \bar{y}_i) = \beta_k (k_{it} - \bar{k}_i) + \beta_l (l_{it} - \bar{l}_i) + \beta_r (r_{it} - \bar{r}_i) + \beta_m (m_{it} - \bar{m}_i) + (v_{it} - \bar{v}_i)\,, \tag{4.4}$$

where the bar sign denotes average over time dimension for each firm.

However, the consistency of the within transformation (or in general the fixed effect model) estimators requires the regressors x_{it} to be strictly exogenous, i.e. x_{is} and v_{it} are uncorrelated for all s, t =1, 2, …, T, although the strict exogenous assumption is considered unrealistic particularly in the manufacturing sector (Grilliches and Mairesse, 1995).[7] Taking first difference might solve the strict exogenous restrictive assumption while at the same time eliminating all individual fixed effects.

$$\Delta y_{it} = \beta_k \Delta k_{it} + \beta_l \Delta l_{it} + \beta_r \Delta r_{it} + \beta_m \Delta m_{it} + \Delta v_{it} \tag{4.5}$$

OLS could be applied for equation (4.5) if we assume that $(v_{it} - v_{it-1})$ and $(x_{it} - x_{it-1})$ are uncorrelated, in addition to the assumption that the unobserved effect is fixed and eliminated by taking the difference. Although this is a weaker assumption than the strict exogeneity assumption in the fixed effect estimator, if $(v_{it} - v_{it-1})$ and $(x_{it} - x_{it-1})$ are correlated we need to use instruments for the first differenced regressors. The advantage of instrumental variable approach depends on the choice of valid instruments (those highly correlated with the regressors but uncorrelated with the error term).[8]

Arellano and Bond (1991) proposed a GMM estimation method where the lagged levels of regressors and the dependent variable are used as instruments for the first differenced equation. The validity of the instruments depends on the extent of correlation between the regressors and the error term. When x_{it} is endogenous **(**i.e.

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[7] It follows that v_{it} and $\bar{v}_i$ are uncorrelated with x_{it} and $\bar{x}_i$ for t = 1, 2,…, T.

[8] Anderson and Hsiao (1982) suggested the two periods lagged dependent variable y_{it-2} or Δy_{it-2} as instruments for a first differenced equation.

x_{it} is correlated with v_{it} and earlier shocks), lagged values dated (t-2) and earlier will be valid additional instruments. When x_{it} is predetermined (i.e. x_{it} and v_{it} are not correlated but x_{it} might be correlated with v_{it-1} and earlier shocks), lagged values dated (t-1) and earlier will be valid instruments in the first differenced equation. If x_{it} is strictly exogenous then the complete time series of x_{it} will be valid instruments in each of the first differenced equations in addition to the dependent variable (t-2) and earlier instruments. These relations are easily testable using standard GMM tests of over-identifying restrictions: the Sargan-Hansen test and the Difference-Sargan test.

The extent of serial correlation is also important in the choice of instruments. If the error terms v_{it} are correlated over time, then the GMM estimator is inconsistent. Thus, for the error term to be serially uncorrelated, the serial correlation of the differenced residual should be first-order, but not second-order. This is also testable with the null of no second-order serial correlation in the first-differenced equations.

However, the GMM method is also usually found providing small and imprecise estimates of capital, and labor coefficients and the overidentifying restriction are frequently rejected (Mairesse and Hall, 1996). Blundell and Bond (1998) argue that in general when the individual series have near unit root properties, the instrumental variable estimators from the first differenced equations can be subjected to series finite sample bias and propose a system GMM that addresses the weak instrumentation problem on the GMM estimation. This new method uses lagged first-difference of inputs and output as instruments in addition to the levels instrument. The system GMM estimator which combines the set of moment conditions in first differences with the additional moment conditions specified for the equation in levels, provides efficient estimators.[9] This is also testable using the Difference-Sargan test. Mairesse and Hall (1996), Blundel and Bond (1998) and Bartlesman and Doms (2000) among others have reviewed the methodologies of estimating production function and constructing TFP further.

[9] Olley and Pakes (1996) proposed a semi-parametric approach using observable micro information, for example investment, as a proxy to controls for the part of the error correlated with inputs. Levinsohn and Petrin (2003) extended this approach by introducing the possibility of using intermediate inputs as a proxy rather than investment. Ackerberg and Caves (2003) and Bond and Soderbom (2004) criticized the proxy method, on the basis of problems of identifying the parameters.

4.2 Estimation Results of the Production Function

The analysis of productivity in this study mainly relies on TFP constructed from estimation of production function using the system GMM methods developed by Blundell and Bond (1998). Thus, we first estimated the production function (equation 4.1) by industry classification and then constructed a TFP series (TFP-GMM hereafter) using industry input coefficients according to equation (4.2). However, we have also used labor productivity measured by output to labor ratio (Y_{it}/L_{it}) primarily as a benchmark for comparison.

Table A1 reports the results of estimating the production functions for 10 industries. In all models we assumed a Cobb Douglas production function with four inputs and introduced year dummies to control for any cyclical effect of the economy. Capital is measured as average capital of the beginning and end year capital stock. Labor is number of employees, but adjusted for quality difference among non-production, production, and seasonal workers. Raw materials represent cost of raw materials, and indirect costs include energy and transport costs, all adjusted with their respective deflators.

We estimated different specifications, the GMM difference and system GMM, with different instruments and tested the validity of the alternative instruments. The GMM difference failed the Sargan-Hansen test for overidentification in most cases, and performs poorly when we look at the input coefficients. The SYS-GMM with instruments dated only t-1 also failed the Sargan-Hansen test of overidentification. The model with instruments t-1 and earlier lags shows symptoms of overfitting due to excessive instruments particularly for industries with small numbers of observations (not reported here).

Two models of the SYS-GMM, i.e. the model with instruments dated only t-2 lag and the model that uses both t-1 and t-2 lags pass the Sargan-Hansen test for overidentification and we find no evidence of second-order serial correlation in the differenced residual. The t-statistics of the estimators are based on robust, finite sample corrected standard errors on the two-step estimates derived by Windmeijer (2000).[10] We then compared these two alternative models using the Difference-

[10] In estimating the system-GMM for industry production functions we used xtabond2 in Stata 9. Unlike the Sargan statistics which is a minimized value of the one-step GMM criterion, the Sargan-

Sargan test since the former is nested within the latter. The Difference-Sargan test can not reject the validity of the additional instruments in all industries since the calculated chi-square value is less than the critical value (see Table A1). As a result, our preferred model is the SYS-GMM that takes t-1 and t-2 lags as instruments, i.e. model II in Table A1. The subsequent analysis on productivity is therefore based on TFP constructed from this model.

5. Comparing Average Productivity across Different Groups

In this section we examine if firm turnover reflects underlying productivity differences among firms. One way to verify the existence of market selection is to look into productivity differentials among continuing, new entrants, and exiting firms. Table 3 reports the average productivity for these different groups based on TFP-GMM and labor productivity for the whole manufacturing sector and by industry.[11] All average productivity measures in the subsequent analysis are unweighted simple averages. Comparing at the aggregated manufacturing level, the continuing firms' average productivity is higher than that of both the entering and the exiting firms in both measures. The entering firms' productivity is also higher than that of the exiting firms in both measures.

Table 3 also reports the average productivity of these different groups of firms for 14 industrial sectors basically at the three-digit level in ISIC classification. The average productivity of continuing firms is higher compared to exiting firms in all but one industry based on both the TFP-GMM and labor productivity. The average productivity of continuing firms is also higher than that of entering firms in 12 and 13 industries out of 14 based on TFP-GMM and labor productivity, respectively.

Hansen statistic reported by *xtabond2* is the minimized value of the two-step GMM criterion function, and is robust to heteroskedasticity or autocorrelation.

[11] The TFP for the whole manufacturing sector is constructed from the sector specific models coefficients of the production function estimation.

Table 3 Comparing average productivity among different groups of firms

Industry	Average TFP (SYS-GMM) continuing	entering	exiting	Average Labor productivity continuing	entering	exiting	Number of observations
All industries	2.562	2.244	2.237	10.33	9.75	9.63	5451
Food	2.859	2.657	2.706	10.49	9.97	10.07	1409
Beverage	3.741	3.292	3.233	11.10	10.83	10.65	151
Textile	3.107	2.957	2.973	10.06	9.89	9.74	259
Apparel	3.398	3.261	3.807	10.07	9.70	10.47	174
Leather	2.705	2.826	2.316	11.15	11.85	10.50	95
Footwear	2.614	2.598	2.273	10.19	10.16	9.33	298
Wood	3.226	2.812	2.957	9.88	8.97	9.18	132
Furniture	2.855	2.576	2.831	9.45	9.03	9.32	874
Paper & printing	3.026	2.841	2.843	10.20	9.97	9.51	390
Chemicals	3.018	2.953	2.790	11.02	10.42	10.02	312
Rubber & plastic	3.138	3.153	3.022	11.14	10.76	10.65	206
Non-metalic	2.977	2.727	2.887	9.68	9.18	9.36	582
Fabricated metal	2.977	2.792	2.895	10.49	9.61	9.47	347
Other industries	-0.185	-0.512	-0.302	11.14	10.34	9.19	214

Notes: The numbers represent the unweighted means of productivity of all firms in the given category and the sample period from 1996 to 2003. The other industries category includes industries such as basic metal, machinery, and vehicle assembly.

Using a dummy regression method following Aw and et al. (1997), we tested the significance of the productivity difference across groups of firms for the aggregated level and by industry. The measured productivity is regressed on a set of dummy variables indicating whether the firm is entering or exiting and on year dummies pooling the data. The continuing firms are excluded from this regression. Therefore the estimated coefficient of the dummy variables can be interpreted as the average productivity differential of the entering and exiting firms in contrast to continuing firms. Negative coefficients of the dummy of entering/exiting firms imply that the entering/exiting firms are less productive than the continuing firms and vice versa.

Table 4 reports the test results for both TFP-GMM and labor productivity. The standard errors are corrected for autocorrelation, i.e. adjusted for intra-firm correlation. In the all industries equation the coefficients of the dummies for entering and exiting firms are negative and significant in both models. This means that the productivity of both the entering and exiting firms is significantly lower than that of continuing firms. According to this estimation, the exiting firms are less productive than the continuing firms by 30 percent and 62 percent based on TFP-GMM and labor productivity, respectively. The entering firms are also on average less productive than continuing firms by 15 percent and 27 percent, respectively. We have also tested the productivity differential between the entering and the exiting firms. Although the average productivity of entering firms is higher than the exiting firms in both measures, the formal test shows that this difference is only significant based on labor productivity.

Table 4 Testing significance of the productivity difference among firm groups

	TFP GMM			Y/L (labor productivity)		
	entering (α)	exiting (β)	F statistics ($\alpha = \beta$)	entering (α)	exiting (β)	F statistics ($\alpha = \beta$)
All industries	-0.152*	-0.301***	F(1, 1603)= 0.42	-0.271***	-0.623***	F(1, 623) = 0.50
	(0.086)	(0.082)	Prob > F = 0.2334	(0.074)	(0.068)	Prob>F= 0.001***
Food	0.059	-0.006	F(1, 440) = 1.04	-0.276**	-0.325**	F(1, 446) =0.05
	(0.039)	(0.042)	Prob > F = 0.3076	(0.138)	(0.135)	Prob > F=0.8237
Beverage	-0.292*	-0.016	F(1, 28) = 0.64	-0.133	-0.545	F(1, 28)= 0.41
	(0.146)	(0.342)	Prob > F = 0.4305	(0.413)	(0.410)	Prob > F= 0.5262
Textile	-0.145	-0.150	F(1, 54) = 0.00	-0.052	-0.429	F(1, 54) = 0.38
	(0.121)	(0.137)	Prob > F = 0.9802	(0.383)	(0.377)	Prob > F =0.5393
Apparel	-0.174	0.201*	F(1, 42) = 3.86	-0.389	0.430	F(1, 45) = 2.67
	(0.118)	(0.118)	Prob > F = 0.056*	(0.285)	(0.289)	Prob > F = 0.109*
Leather	0.095	-0.697***	F(1, 16) = 5.81	1.044***	-1.644***	F(1, 16) = 21.93
	(0.162)	(0.204)	Prob> F =0.028**	(0.302)	(0.383)	Prob>F=0.0002***
Footwear	-0.075	-0.107	F(1, 89) = 0.08	0.121	-0.821***	F(1, 90) = 6.74
	(0.074)	(0.079)	Prob > F = 0.780	(0.243)	(0.246)	Prob> F =0.011***
Wood	-0.109	-0.086	F(1, 43) = 0.01	-0.259	-0.631**	F(1, 45) = 0.88
	(0.153)	(0.177)	Prob > F = 0.941	(0.240)	(0.269)	Prob > F = 0.3545
Furniture	-0.096*	-0.168***	F(1, 293) = 0.75	-0.180	-0.193	F(1, 296) = 0.00
	(0.055)	(0.050)	Prob > F = 0.386	(0.153)	(0.125)	Prob > F = 0.9445
Paper &	-0.025	-0.192	F(1, 88) = 0.88	-0.033	-0.746***	F(1, 88) = 2.21
printing	(0.095)	(0.114)	Prob > F = 0.351	(0.252)	(0.306)	Prob > F = 0.1407
Chemicals	0.112	-0.161*	F(1, 64) = 4.42	-0.418	-0.961***	F(1, 64) = 2.35
	(0.103)	(0.098)	Prob >F =0.039**	(0.301)	(0.278)	Prob > F = 0.1302
Rubber &	-0.025	-0.135	F(1, 41) = 0.17	-0.299	-0.336	F(1, 42) = 0.00
plastic	(0.147)	(0.204)	Prob > F = 0.685	(0.332)	(0.340)	Prob > F = 0.9449
Non-metallic	-0.093	0.079	F(1, 187) = 2.53	-0.301*	-0.263*	F(1, 188) = 0.03
	(0.076)	(0.074)	Prob > F = 0.114	(0.168)	(0.153)	Prob > F = 0.8547
Fabricated	0.116	-0.048	F(1, 139) = 1.55	-0.282	-0.785***	F(1, 139) = 1.78
metal	(0.092)	(0.088)	Prob > F = 0.215	(0.267)	(0.247)	Prob > F = 0.1841
Other	-0.177*	-0.120	F(1, 66) = 0.21	0.027	-1.957***	F(1, 68) = 10.54
industries	(0.099)	(0.126)	Prob > F = 0.647	(0.472)	(0.413)	Prob> F =0.002***

Notes: In all estimations the dependent variable is productivity (i.e. TFP GMM, or Labor productivity) of each firm by year. The main explanatory variables are two dummies that show whether the firm is exiting or entering, while continuing firms are excluded. Year dummies are also included. Figures in parentheses under each coefficient represent standard errors. These standard errors are corrected for autocorrelation that arise from repeated observations of the same firms. Significance at the one percent, five percent and ten percent level is indicated by ***, **, and * respectively.

The test of significance of the average productivity difference by industry is also given in Table 4. We found 12 and 13 negative coefficients out of 14 industries for exiting firms based on TFP-GMM and labor productivity, respectively. However, this difference is significant in only 4 and 9 industries, respectively.[12] The coefficient of entering firms is also found to be negative in 10 and 11 industries out of 14, based on TFP-GMM and labor productivity, respectively. These are only significant in 3 industries based on both measures of productivity.

Obviously there is a concern related to the measurement of TFP from production functions based on gross value of production. In most gross value of production functions the capital coefficient is found to be low in magnitude and often insignificant. As a result, large firms might appear to be more productive than small firms. To address this concern we estimated the value added based production function for the whole manufacturing sector using the SYS-GMM method (not reported here for brevity).[13] This estimation gives the labor and capital coefficients 0.83 and 0.37 respectively, and both are highly significant. We then constructed TFP from the value added based SYS-GMM estimation using equation (4.2). We used the dummy regression method when looking at the productivity differential among continuing, entering and exiting firms, while at the same time testing this difference. Both the entering (-0.199) and exiting (-0.149) firms' coefficients are negative and highly significant, implying that the new entrants as well as the exiting firms are on average less productive than the continuing firms. Hence, the previous finding that exiting and entering firms are on average less productive than continuing firms is robust even when we use value added rather than gross value of production; the former improves the coefficient of the capital.

So far we have examined if the turnover patterns reflect underlying differences in productivity, relying on the comparison of unweighted average productivity among continuing, entering, or exiting firms. All measures of productivity show that the continuing firms' average productivity is higher than that of the exiting firms, and

[12] In our comparison of the industrial level productivity differences, we consider the significance of the coefficients at least at the 10 percent level.
[13] In estimating the value-added based production function with SYS-GMM method we use xtabond2 with instruments only t-2, since the validity of this instrument is not rejected by Hansen-Sargan test of overidentifying restriction and we find no evidence of second-order serial autocorrelation. The t-statistics are based on robust, finite sample corrected standard errors.

this is significant at the aggregated level and in some industries. This shows that the exiting firms are on average less productive than the surviving firms, and provides some evidence of a market selection process in the Ethiopian manufacturing sector. The productivity of new entrants is also lower compared to the continuing firms, implying that new entrants join the industry with a lower rank of productivity than the incumbents, which is contrary to the vintage effect prediction.[14]

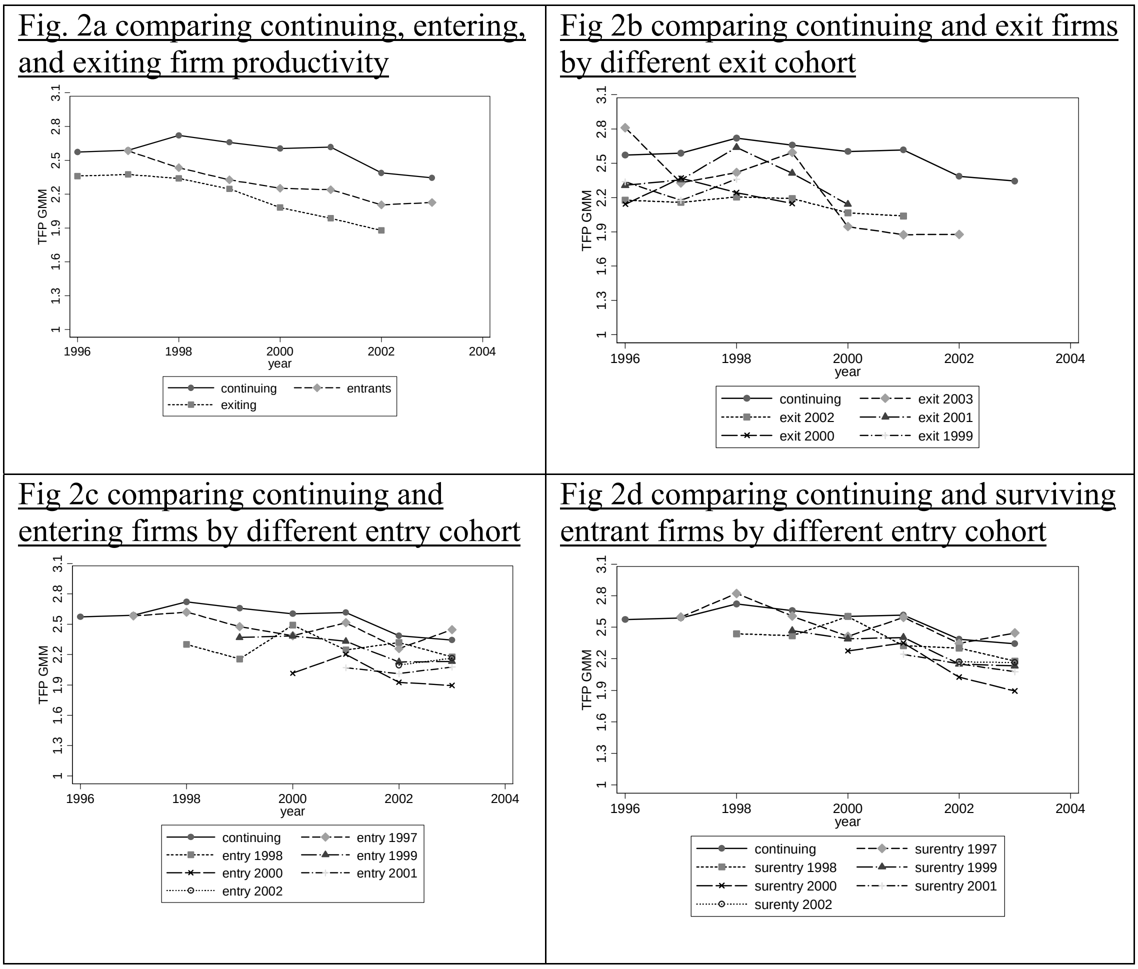
However, this simple average productivity comparison is crude in the sense that it doesn't show the evolution of productivity over time. The literature on market selection points out that the benefits of the resource reallocation due to exit and entry are realized over time. Hence, it is useful to show the pattern of productivity over time across different groups at least to examine the "shadow of death" effect argument and the catching-up or learning process. Moreover, without looking at the pre-exit and post-entry productivity of firms by entry and exit cohorts, it is difficult to determine whether exiting firms are replaced by new firms that are more productive. Therefore we next look at the pattern of average productivity of the continuing, entering, and exiting firms by year and entry and exit cohorts.[15]

Figure 2 presents the time trend of average productivity of the continuing, entering, and exiting firms based on TFP-GMM. Figure 2a gives the average productivity pattern of continuing firms and all cohorts of entering and exiting firms. There are a number of important observations to be noted in this figure. First, the continuing firms' average productivity is higher than that of both new entrants and exiting firms in all years. Second, the entering firms' productivity is also higher than that of the exiting firms in all years. Third, the productivity of exiting firms declines and the difference between continuing and exiting firms' productivity widens over time. This is consistent with the "shadow of death" effect argument that firm exit is not random but the result of persistent decline in productivity.

[14] Our results are consistent with most previous studies. Hahn (2000), Liu (1993), Liu and Tybout (1996) and Aw et al. (1997) documented that the continuing firms' productivity is higher compared to both the exiting and entering firms.

[15] The effect of exit and entry on productivity growth will be discussed in detail in Section 7.

Figure 2: Productivity pattern of continuing, entering, and exiting firms by year



Notes: For the definitions of continuing, entering, and exiting firms see Section 3. In Figure 2d surentry1997 to surentry2002 abbreviates surviving new entering firms between 1997 and 2002. Surviving new entrants are those firms that enter the data set after 1996 and stay in the sample until the end of the sample period, i.e. 2003.

To clearly show the evolution of productivity in the pre-exit and post-entry periods further, we present the patterns of productivity by entry and exit cohorts. Exit firms are grouped into different categories according to their exit year by defining a year equal to zero when the firm exits. We then calculated average TFP of the firms in each category in time periods (-1, -2, -3 …) to show the pre-exit performance of the same exit cohort. Figure 2b provides the patterns of productivity of exiting firms by exit cohort along with the productivity of continuing firms. As we can observe from this figure, the exiting firms face a continuous decline in productivity at least 2-3 years before exit. The difference in productivity compared to continuing firms also widens over time. This confirms that exit is not random but a result of a persistent decline in productivity, and provides strong evidence of the “shadow death” effect.

Similarly, in order to see the post-entry productivity evolution we grouped new firms according to birth year and computed average productivity of the same birth year firms in periods (1, 2, 3…). Figure 2c gives the pattern of average productivity of all entering firms by entry cohort along the average productivity of continuing firms. Most of the entry cohorts start at lower levels of productivity when they join the industry. Unlike the exit cohorts, the general pattern of the average productivity of entry cohorts is that the gap to continuing firms shrinks rather than widens.

The new entering firms themselves are, however, heterogeneous in the sense that some of them improve productivity and survive, and the less productive ones exit. Hence, to further examine whether convergence of productivity takes place, we present Figure 2d that compares the trends of productivity of continuing firms with successful entrants by entry cohort.[16] The convergence in productivity is more evident in this figure particularly for early entrant firms (i.e. 1997 and 1998 entrants). This shows not only the presence of a learning process, but also the required time lag for catching-up.

Finally, we have examined average productivity difference by ownership (see Table 5). Surprisingly, the public firms' average productivity is higher than that of the private firms in both measures of productivity and in all years except one. This is partly explained by the nature of privatization and the immaturity of the private sector. In actual practice the government tends to sell firms that are less efficient (i.e. less profitable) and retain firms with better efficiency. In addition, most of the privatized firms undergo an adjustment period that might worsen productivity at least for some years following the privatization. Given the previous restriction on the private sector, a large number of the firms in this sector are new. From our previous finding we know that most of the new firms start with a lower rank of productivity relative to the incumbents. But the difference in productivity might also indicate differences in access to various resources. The private firms are mostly new and small, might have less access to resources such as finance, and constrained regarding growth and productivity improvement.

[16] A successful entrant here is defined as a firm that entered the data set after 1996 and remained in the data set until the end of the sample period i.e. 2003.

Table 5 Average productivity by ownership and year

	TFP GMM		Y/L		Number of firms		
	public	private	public	private	public	private	total
1996	2.45	2.48	10.62	9.90	139	406	545
1997	2.54	2.47	10.58	9.92	127	491	618
1998	2.71	2.51	10.70	10.03	131	516	647
1999	2.70	2.43	10.58	9.95	126	511	637
2000	2.61	2.36	10.52	9.97	118	517	635
2001	2.85	2.30	10.83	9.94	115	552	667
2002	2.56	2.15	10.49	9.70	121	688	809
2003	2.54	2.14	10.34	9.56	122	693	815

Notes; All numbers represent unweighted mean of productivity.

6. The Decision to Exit

The next obvious step is to examine whether the productivity level helps predict exit after controlling other firm attributes. Why do firms decide to exit? The literature tells us that firms' decision to continue in or exit from business basically depends on the perception of the future profitability of their assets. However, other firm characteristics such as firm size, age, and capital intensity could also affect the exit decision. Firm survival is positively related to firm size and age as these variables themselves are results of a previous market selection process (Jovanovic, 1982). Capital intensity might also capture the future profitability of the firm; therefore it is expected to be positively associated with firm survival.

Following Olley and Pakes (1996), we formulate a binary exit decision model as a function of productivity and other firm attributes. We define X_t as an indicator function that equals one if the firm exits and zero otherwise. The exit decision can then be stated as:

$$X_t = \begin{cases} 1 & \text{if } x_t < \bar{x}_t(a_t) \\ 0 & \text{otherwise,} \end{cases} \tag{5.1}$$

where $\bar{x}$ denotes the minimum productivity required for staying in business and a_t denotes other firm attributes such as size, age, and capital-labor ratio.

We estimated a probit model pooling the data where the firm decision to exit is a dependent variable that takes a value of one if the firm exits prior to the end of the sample period and zero otherwise.[17] The categorical variable that represents the exit decision is regressed on explanatory variables such as TFP-GMM, size, age, and capital intensity. Size is measured by employment, capital intensity by capital to labor ratio, and age is calculated as the current year minus the year of establishment plus one, all in logarithm form. We used the initial values of size, age and capital intensity, assuming that the initial characteristic of a firm affects its decision to exit at some point in the next 1 to 7 years, depending on its duration in the data. We included industry and year dummies in all estimations. Since the effect of productivity on the exit decision is our main interest we also estimated the same model but substituted TFP-GMM with labor productivity (Y/L) to check for robustness of our results.

The results of the probit model are presented in Table 6. The reported standard errors are robust and corrected for autocorrelation that could arise from repeated observations of the same firm. The first two columns give the probit estimation results of the unconditional exit decision where only productivity and year and industry dummies are included in the model. The next two columns give the results from models that control other firm attributes in addition to industry and year dummies. For ease of interpretation we present the marginal effect calculated at the mean of each variable, instead of the probit coefficients. Thus, the estimates should be interpreted as the change in the probability of exit as a response to a one-unit change in the explanatory variables, since all the regressors are continuous variables.

The unconditional estimations for both productivity measures provide negative and highly significant marginal effects of productivity on the exit decision. The magnitude of the marginal effect is -0.037 and -0.077 based on TFP-GMM and labor productivity respectively. When we control other firm attributes, the magnitudes of the marginal effect of productivity decline marginally to -0.025 and -0.041 respectively, but all are still negative and highly significant. According to the conditional exit estimation results, the probability of exit increases by 2.5 and 4.1

[17] This categorical variable is time invariant in the sense that those firms exiting in any year before the end of the sample period are treated equally and assigned a value equal to one for all periods they are present in the data set.

percent for a one percentage decline in productivity based on TFP-GMM and labor productivity respectively. Hence, the probit model confirms the existence of a market selection process in which the less efficient dies and the more efficient survives even after controlling for other firm characteristics.

Table 6 Probit estimation of the decision to exit

	Effect of productivity			
	unconditional		conditional on other firm attributes	
	TFP-GMM	Y/L	TFP-GMM	Y/L
	dF/dx	dF/dx	dF/dx	dF/dx
Productivity	-0.037***	-0.077***	-0.025**	-0.041***
	(0.014)	(0.009)	(0.013)	(0.009)
Size			-0.145***	-0.134***
			(0.014)	(0.014)
Age			-0.056***	-0.054***
			(0.014)	(0.014)
K/L			-0.015**	-0.007
			(0.006)	(0.007)
# of observations	4551	4628	4545	4611
Log-likelihood	-2524.27	-2494.34	-2165.68	-2190.44

Notes: The dependent variable in all estimations is a dummy variable that indicates exit with a value equal to one, and zero otherwise. All explanatory variables are in logarithmic form. Size, age, and capital intensity do not vary by year since they represent the initial values when the firm first appeared in the data. In all estimations we control both year and industry variation. The reported estimates (dF/dx) are the marginal effects calculated at the mean of each variable. The numbers in parentheses are standard errors corrected for autocorrelation. Significance at the one percent, five percent and ten percent level is indicated by ***, **, and * respectively.

Both models show that firm size, age, and capital intensity are negatively correlated with exit. In other words, the probability of survival increases with size, age, and capital intensity. Size is by far the largest determinant of the exit decision, and is highly significant. The marginal effect of size is between -0.13 and -0.14.5 depending on the specification, which is more than three times the effect of productivity on the exit decision. This implies that, other things being equal, the smaller the firm the higher the probability of exit. Age also takes a negative coefficient and is highly significant, which means that the probability of death is higher among younger firms, other things being equal. The capital intensity is also negative in both models, but only significant in the model with TFP-GMM, suggesting that firms with higher capital intensity have a higher probability of surviving.

7. The Effect of Firm Turnover on Aggregate Productivity Growth

We now turn to investigate the effect of resource reallocation and particularly turnover on industry productivity growth. The level of productivity in an industry in year t can be aggregated using plant's share of industry as follows:[18]

$$\ln TFP_t = \sum \theta_{it} \ln TFP_{it} \,, \tag{6.1}$$

where θ_{it} is the share of the i^{th} plant in the industry output.

Then the industry growth of TFP from period t-1 to period t is measured as:

$$\Delta \ln TFP_t = \ln TFP_t - \ln TFP_{t-1} \,. \tag{6.2}$$

Turnover based industry productivity gains can come from two sources: productivity growth from continuing firms and net productivity gains from entering and exiting firms in the industry. We follow the methodology developed by Baily et al. (1992) in decomposing productivity growth among firms that continue in the industry, new entrants and those who exit.[19] The change in productivity in an industry from period t-1 to t can be found in:

$$\Delta \ln TFP_t = \sum_{i \in C} (\theta_{it} \ln TFP_{it} - \theta_{it-1} \ln TFP_{it-1}) + \left(\sum_{i \in N} \theta_{it} \ln TFP_{it} - \sum_{i \in X} \theta_{it-1} \ln TFP_{it-1} \right), \tag{6.3}$$

where C, N, and X represent continuing, entering and exiting firms respectively.

The productivity among the continuing firms can be decomposed further into a pure improvement in productivity and the effect of reallocation of market share from inefficient to efficient firms in the industry.

$$\sum_{i \in C} (\theta_{it} \ln TFP_{it} - \theta_{it-1} \ln TFP_{it-1}) = \sum_{i \in C} \theta_{it-1} \Delta \ln TFP_{it} + \sum_{i \in C} (\theta_{it} - \theta_{it-1}) \ln TFP_{it}$$

Thus, substituting this into equation (6.3) yields:

[18] The whole manufacturing productivity can also be aggregated in the same manner using each industry output share as weights.

[19] Note that there are other modified versions of this decomposing method. For example Foster, Haltiwanger, and Krizan (2001) separate the within and between effects from the cross/covariance effect.

$$\Delta \ln TFP_t = \sum_{i\in C}\theta_{it-1}\Delta\ln TFP_{it} + \sum_{i\in C}(\theta_{it}-\theta_{it-1})\ln TFP_{it} + \sum_{i\in N}\theta_{it}\ln TFP_{it} - \sum_{i\in X}\theta_{it-1}\ln TFP_{it-1} \tag{6.4}$$

The first two terms in equation (6.4) show the contribution of the continuing firms. The first term represents the "within-plant" component of change in productivity weighted by initial shares in the industry, and the second term reflects share effect, i.e. the contribution from changes in output share. The third and fourth terms represent the contribution to TFP growth from entrants and those exiting the industry respectively. The net effect of the third and fourth terms on productivity growth is known as the turnover effect.

In constructing the annual productivity growth of different groups of firms according to equation (6.4), we need to redefine the classification of continuing, entering, and exiting firms. In this sub-section, therefore, continuing firms (or incumbent firms) are defined as firms that entered the data set before the reference year and that did not exit until the reference year.[20] For instance, firms defined as incumbent in 1989 are those that entered before 1989 and stayed in the data at least until 1989. New entrants on the other hand are defined as firms that entered in the reference year. This means that 1989 entrants are those firms that began operations in 1989 and not prior or later than 1989. The firms that entered in 1989 are considered incumbent firms in 1990 unless they exited in 1990. Exit firms are defined as firms that exited in the reference year.

Table 7 reports the cross year average productivity growth of 14 industries and aggregate manufacturing based on TFP-GMM.[21] The all industry aggregate productivity growth is the weighted average of industry productivity growth based on share of output of each industry of total manufacturing output. The average annual productivity growth for all industries from 1996 to 2003 is 9.3 percent. The decomposition of the TFP growth shows that the net effect of turnover on manufacturing productivity growth is 9.7 percentage points, while the average annual

[20] The definition here is a bit different from the previous definition in Section 3, since in this current section we are dealing with year by year turnover and productivity change. Liu and Tybout (1996) use a similar approach based on annual data. This decomposition method is basically that of Baily et al. (1992), except our data is annual and theirs was five year interval.

[21] The average productivity growth for 14 industries and the aggregate manufacturing sector is calculated from the year by year productivity growth. For brevity we only report the averages but not the year by year.

productivity growth of incumbent firms is almost zero (-0.004). This means that the contribution of turnover to productivity growth accounts for above 100 percent of total productivity growth. This is because the entering firms in their first year are on average more productive than dying firms in their last year, and implies that exiting firms are replaced by new firms that are more productive. Decomposing further the productivity growth among incumbents, the share effect is positive (0.005), while the within firm productivity growth is negative (-0.009).

Table 7 Decomposing productivity growth

Industry	total TFP growth	Incumbent's productivity growth: within firm effect	share effect	total incumbents	net entry effect
All industries	**0.093**	**-0.009**	**0.005**	**-0.004**	**0.097**
Food	0.042	-0.081	0.050	-0.031	0.073
Beverage	0.025	0.021	-0.045	-0.024	0.048
Textile	0.308	-0.016	0.160	0.144	0.165
Apparel	0.045	-0.083	-0.029	-0.113	0.158
Leather	0.153	0.009	0.038	0.047	0.106
footwear	0.318	0.068	0.200	0.268	0.050
Wood	0.072	-0.036	0.130	0.094	-0.022
Furniture	-0.108	-0.153	-0.002	-0.155	0.047
paper & printing	0.016	-0.154	0.113	-0.041	0.057
Chemicals	-0.024	-0.117	-0.060	-0.177	0.153
rubber & plastic	0.099	0.068	-0.203	-0.136	0.235
non-metalic	0.032	-0.074	-0.102	-0.176	0.208
Fabricated metal	-0.065	-0.143	-0.127	-0.269	0.204
Other industries	-0.187	-0.152	-0.018	-0.171	-0.016

When we look into industry comparison, four industries (furniture, chemical, fabricated metal, and others) exhibited negative annual average productivity growth in the sample period. However, five industries (textile, leather, footwear, wood, and rubber and plastic) achieved an above 7 percent annual average productivity growth. These are the four industries (excluding rubber and plastic) that also exhibit a positive productivity growth among incumbents. The turnover effect on productivity growth is positive in all industries, except two, implying that entering firms are more productive than exiting firms in most industries. The turnover effect is not only positive but also higher in magnitude than the total effect of incumbents (the sum of within-plant and share effect TFP growth) in most industries. For the incumbent firms the share effect is higher than the within-plant productivity growth, implying that the effect of resource reallocation on industry aggregate productivity growth, whether by entry and exit or by market share reallocation among continuing firms, is positive.

Our study shows that the major source of aggregate productivity growth in Ethiopian manufacturing is the net effect of entry, i.e. the higher productivity of new entrants than of dying firms. This finding is consistent with previous studies particularly those documenting high firm turnover. Bartelsman et al. (2004) found a high contribution of turnover on productivity growth in transition economies. Hahn (2000) also reported a very large effect of entry and exit on aggregate TFP growth in Korea, accounting for between 40 percent and 65 percent depending on the period considered. However, the effect of turnover on productivity growth in most industrialized and some Latin America countries is small. Liu and Tybout (1996) on Colombia, Baily et al. (1992) on USA, and Bartelsman et al. (2004) on most OECD members found small effect of turnover on productivity growth and argue that entering firms in their first year are not much more productive than dying plants in their last year, and neither group accounts for much output. Productivity growth in these economies is largely driven by share effect (Liu and Tybout, 1996 and Baily et al., 1992) or by within firm performance (Bartelsman et al., 2004).

8. Conclusions

In this paper we provide empirical evidence on firm turnover and productivity differentials in Ethiopian manufacturing based on firm level industrial census data. Examining the market selection process is relevant given the sequence of reforms undertaken to liberalize, deregulate markets, and eliminate much of the previous competition-hindering protections. Overall, our study reveals a massive reallocation of resources in Ethiopian manufacturing, with substantial entry and exit, failure of many new firms, and expansion of successful ones. Market selection process is at work, and productivity differences across firms are reflected in the turnover pattern. We have also found a higher aggregate productivity growth over the sample period, mainly driven by firm turnover. Further details of our findings are as follows:

First, firm turnover is substantial with about a 22 percent annual average turnover rate over the 1996-2003. Firm entry largely out-paced exit, thus making net entry positive. Firm churning in Ethiopian manufacturing is large in comparison to industrial economies, mainly reflecting the dominance of light industries with low start-up capital and the transition nature of the economy from a command to a market oriented one. The turnover rate is very high among smaller firms and decreases with size. The high turnover rate affects considerably the mix of firms and resource reallocation. The new entrants (less than five years old) account for about a quarter of total employment and output, and half of all firms. Job destruction and output contraction due to firms that exit within 5 years account between 9 and 15 percent.

Second, the mortality rate is very high among new entrants, particularly in the first three years after entry: more than 60 percent exit within this period. This shows that the entering cohorts themselves undergo a shakedown period and that market selection is even harsher for them.

Third, the pattern of firm turnover partly reflects productivity differences across firms, i.e. evidence of market selection. On average, exiting firms are less productive than continuing firms and entering firms. The productivity level also helps to predict exit after controlling other firm characteristics such as size, age and capital intensity. The productivity of exiting firms was less than that of continuing firms, and this difference increased over time. Hence, exit is not random but follows from persistent decline in productivity. This is consistent with the “shadow of death” effect argument. Also firm survival is positively associated with size and age.

Fourth, public firms are on average more productive than private firms. This is partly explained the nature of privatization and the short history of the private sector. The government tends to privatize firms with lower profitability, and these firms usually undergo an adjustment period. Most of the firms in the private sector are new, and firms start with lower ranks of productivity relative to the incumbents.

Fifth, the Ethiopian manufacturing sector exhibits an annual average productivity growth of about 9.3 percent from 1996 to 2003, with entry and exit of firms being the major source of productivity growth. This study shows that the higher productivity of new entrants in their first year relative to dying firms in their last year significantly contributed to the higher productivity growth in the Ethiopian manufacturing sector and implies that exiting firms are replaced by new, more productive firms. The contribution of incumbents to total productivity growth is, however, approximately zero.

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Table A1 The system GMM estimates of production functions by industry

		Model I [a] (with only t-2 lag as instruments)					Model II [b] (With t-1 and t-2 lags as instruments)					N*T [c] (N)	Sargan-Difference test [d]
Industry	Inputs	Coeff.	std. error	tests [e]	statistic	p-value	Coeff.	std. error	tests	statistic	p-value		Statistic
Food & beverage	Capital	-0.01	0.02	S-Hansen	83.61	0.05	0.02	0.02	S-Hansen	90.64	0.121	1539 (470)	7.03
	Labor	0.12**	0.06	m1	-4.47	0	0.20***	0.04	m1	-4.58	0		
	R. mat	0.89***	0.04	m2	0.41	0.68	0.81***	0.04	m2	0.12	0.92		
	Ind. cost	0.12**	0.05				0.08***	0.02					
Textile & apparel	Capital	-0.04	0.08	S-Hansen	59.01	0.653	0.01	0.05	S-Hansen	66.71	0.768	420 (98)	7.7
	Labor	0.11	0.10	m1	-4.07	0	0.23**	0.10	m1	-4.02	0		
	R. mat	0.68***	0.07	m2	-1.9	0.057	0.58***	0.07	m2	-1.75	0.08		
	Ind. cost	0.13	0.10				0.11	0.11					
Leather & footwear	Capital	0.03	0.07	S-Hansen	50.98	0.881	0.09**	0.05	S-Hansen	70.46	0.658	392 (107)	19.48
	Labor	0.06	0.08	m1	-4.83	0	0.09	0.07	m1	-4.92	0		
	R. mat	0.70***	0.08	m2	0.27	0.787	0.65***	0.04	m2	0.16	0.872		
	Ind. cost	0.17*	0.09				0.12**	0.06					
Wood & furniture	Capital	-0.01	0.04	S-Hansen	74.11	0.182	0.09*	0.05	S-Hansen	90.08	0.129	987 (338)	15.97
	Labor	0.13	0.14	m1	-6.46	0	0.06	0.07	m1	-6.49	0		
	R. mat	0.71***	0.06	m2	-0.72	0.474	0.63***	0.04	m2	-0.58	0.561		
	Ind. cost	0.22***	0.07				0.16***	0.05					
Paper & printing	Capital	0.02	0.02	S-Hansen	42.74	0.981	0.00	0.02	S-Hansen	57.22	0.947	390 (89)	14.98
	Labor	0.22**	0.09	m1	-3.76	0	0.27***	0.09	m1	-3.68	0		
	R. mat	0.69***	0.11	m2	-0.92	0.359	0.64***	0.07	m2	-1.02	0.309		
	Ind. cost	0.02	0.10				0.08	0.06					
Chemicals	Capital	-0.03	0.10	S-Hansen	38.49	0.995	-0.02	0.07	S-Hansen	47.99	0.995	311 (65)	9.5
	Labor	0.12	0.14	m1	-3.35	0.00	0.17*	0.10	m1	-3.45	0.001		
	R. mat	0.64***	0.15	m2	-0.66	0.508	0.74***	0.09	m2	-0.78	0.437		
	Ind. cost	0.25**	0.11				0.13*	0.08					

Table A1 continued …

Industry	Inputs	Model I Coeff.	Model I std. error	Model I test	Model I statistic	Model I p-value	Model II Coeff.	Model II std. error	Model II test	Model II statistic	Model II p-value	N*T (N)	Sargan-Difference test Statistic
Rubber & plastic	Capital	0.09	0.27	S-Hansen	17.61	1	-0.06	0.16	S-Hansen	26.7	1	203	9.09
	Labor	0.36	0.36	m1	-2.78	0.005	0.29	0.26	m1	-2.55	0.011	(42)	
	R. mat	0.62***	0.13	m2	-0.27	0.785	0.57***	0.09	m2	-0.92	0.355		
	Ind. cost	-0.01	0.28				0.16**	0.08					
non-metalics	Capital	-0.02	0.08	S-Hansen	60.92	0.586	0.03	0.05	S-Hansen	71.14	0.636	566	10.22
	Labor	0.40**	0.18	m1	-4.01	0	0.33	0.08	m1	-3.98	0	(188)	
	R. mat	0.44***	0.06	m2	-0.89	0.371	0.47	0.05	m2	-0.85	0.395		
	Ind. cost	0.25***	0.07				0.20	0.04					
Fabricated metal	Capital	0.11	0.09	S-Hansen	36.73	0.997	0.04	0.09	S-Hansen	60.5	0.888	346	23.77
	Labor	-0.09	0.23	m1	-2.97	0	0.30**	0.15	m1	-2.65	0.008	(140)	
	R. mat	0.60***	0.10	m2	0.77	0.442	0.57***	0.09	m2	-0.08	0.934		
	Ind. cost	0.25**	0.12				0.17***	0.07					
Other industries	Capital	0.29	0.22	S-Hansen	22.98	1	0.34**	0.15	S-Hansen	37.24	1	211	14.46
	Labor	0.11	0.21	m1	-2.65	0.008	-0.03	0.23	m1	-2.56	0.01	(67)	
	R. mat	0.68***	0.12	m2	-0.37	0.712	0.70***	0.11	m2	-0.1	0.924		
	Ind. cost	0.05	0.14				0.03	0.16					

Notes: The difference between Model I and Model II is that the first uses only t-2 lag instruments while the latter uses both t-1 and t-2 lags for the differenced equation. The dependent variable for the production functions in both estimations is output. All variables are in logarithmic form. Year dummies are also included in all estimations. Significance at the one percent, five percent and ten percent level is indicated by ***, **, and * respectively.

[a] The instrument set for the differenced equation consists of all inputs in period t-2 only. The instrument set for the level equation on the other hand consists of all inputs in period t-1.

[b] The instrument set for the differenced equation consists of all inputs in period t-1 and t-2. The instrument set for the level equation on the other hand consists of all inputs in period t-1.

[c] N*T represents the number of observations while N in the parentheses represents the number of firms.

[d] The Sargan-Difference test is a test of the validity of additional instrument between Model I and Model II. The reported statistics in all industries are the calculated chi-square values at 12 degrees of freedom. The critical value at which the null that the validity of additional instruments should be rejected with 12 degrees of freedom is above 21.02 and 26.2 for the 5 percent and 1 percent level of significance, respectively.

[e] The S-Hansen test is the Sargan-Hansen test on the validity of over-identifying restrictions. m1 and m2 are first and second order serial correlation tests, respectively.

ESSAY II

Do Size and Age Matter?
Growth of Firms in Ethiopian Manufacturing

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Abstract

This study examines the relationships between firm growth and firm size, age, and labor productivity, using annual census based panel data on Ethiopian manufacturing firms. Unlike most previous studies in sub-Saharan Africa, this study explicitly addresses the ongoing statistical concerns in the firm growth models such as sample censoring, regression to the mean, and unobserved heterogeneity. Overall, our empirical results indicate that firm growth decreases with size. This relation is not affected by fluctuations or measurement error in size and by controlling unobserved heterogeneity. It is also robust after correcting for sample censoring and explicitly considering the growth rate of exit firms to be -100 percent in the exit period. This suggests not only that smaller firms have faster rates of employment growth than larger firms, but also that growth rates of smaller firms are large enough to compensate for their attrition rates. The negative relation between growth and age predicted by the learning process is found to impact only younger firms at the early stage 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 process through growth differential. Capital intensity, location in the capital city, and public ownership also affect firm growth positively.

Keywords: Firm growth, size and age, unobserved heterogeneity, manufacturing, Africa.

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1. Introduction

Firm growth in general and employment generation in particular in the manufacturing sector have been a focal point of most industrial policies. In Africa, as in other developing countries, large firms are criticized particularly by the international aid agencies for not creating enough jobs, while micro and small firms are singled out as the main source of job creation and engine of development (Biggs and Srivastava, 1996). However, this is empirically controversial at least in sub-Saharan Africa (Bigsten and Söderbom, 2005). Hence, understanding the characteristics of fast growing firms is particularly important for policies that aim at creating jobs.

How does growth vary across firms? Do small firms grow faster than large firms? Which attributes of firms other than size affect firm growth? 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, show no heteroskedasticity with size, and the concentration of size distribution increases with time. The two common empirical implications of this law are: fitting the size distribution to test for log-normal distribution, and directly testing the relationship between growth and 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 (Evans, 1987a,b; Hall, 1987; Kumar, 1985; Dunne and Hughes, 1994). Several studies have also documented a negative relationship between firm growth and age (Evans, 1987a; Hall, 1987; Dunne and Hughes, 1994). Caves (1998) reviewed the empirical findings in developed countries.

However, the nature of the association between firm growth and size in African manufacturing is far from certain. Bigsten and Söderbom (2005) summarized the emerging empirical evidence in sub-Saharan Africa (SSA, henceforth). 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 less clear cut evidence for convergence in size in Ghana; there the rate of growth is highest for medium sized firms. Harding, Söderbom, and Teal (2004) found no evidence of correlation between growth and size in their regression of growth on mean size. Biesebroeck (2005) found that large firms grow more rapidly than small firms conditional on other covariates using data on nine Sub-Saharan African countries.[1]

This paper extends the previous empirical studies on firm growth in SSA in the following context. 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, it introduces a recently developed system GMM method to control the effect of unobserved heterogeneity and endogeneity problems 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 error in size. However, 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 through growth differential. 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 3 discusses the data source of the study and provides a descriptive analysis. Section 4 gives the basic econometric framework and empirical results. Section 5 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.

2. Literature Review on Models of Firm Growth

According to the standard neo-classical theory, size is determined by the same factors that affect 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

[1] The nine SSA countries covered in most of the above cited studies are Kenya, Ghana, Zambia, Zimbabwe, Cote d'Ivoire, Ethiopia, Burundi, Tanzania, and Cameroon. Most of these studies are based on the database provided by the RPED 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 complete size distribution of firms in homogeneous-product industries (Evans 1987b).

minimum cost is achieved. This means that in a perfect competitive market, firms with a U-shaped average cost curve should grow until they reach the lowest point of the curve, which implies that the size distribution will be narrowly dispersed.[3] However, the scale corresponding to minimum cost need not be the same for different firms even if in the same industry, since firms can have the same minimum cost, but have varying outputs. 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 was directed towards a stochastic process, relying on a purely statistical argument, namely that the usually observed skewed size distribution of firms could be 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 concentration of size distribution increases with time. Firms grow each year following random drawing from a distribution of growth rates thus small and large firms have on average identical growth chances. 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.

Two major empirical implications of Gibrat's law have been commonly tested: 1) fitting the size distribution and testing if the limiting size distribution of firms belongs to the family of skewed distributions (e.g. lognormal, Pareto, Yule etc.), and 2) directly testing the null hypothesis that firm growth is independent of size by looking at the relation between firm size and growth over successive years.

The LPE, or Gibrat's law, that asserts that growth is random and determined by a stochastic process, can be formally stated following Sutton (1997) as:

$$S_{it} - S_{it-1} = \varepsilon_{it} S_{it-1}, \qquad (2.1)$$

where S_{it} denotes the size of firm i at time t, and ε_{it} denote the proportionate rate of growth between period (t-1) and period t, and equivalently,

[3] Some other theories have been developed based on different assumptions of the scale of economies increasing return, decreasing return and constant cost curves (for example, 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.

$$S_{it} = (1+\varepsilon_{it})S_{it-1} = S_{i0}(1+\varepsilon_{i1})(1+\varepsilon_{i2})...(1+\varepsilon_{it}) .$$

In a short time period ε_{it} can be justified to be small, hence $\ln(1+\varepsilon_{it}) = \varepsilon_{it}$ and taking logs in both sides gives:

$$\ln S_{it} = \ln S_{i0} + \varepsilon_{i1} + \varepsilon_{i2} ... + \varepsilon_{it} \cong \ln S_{io} + \sum_{t=1}^{T} \varepsilon_{it} . \qquad (2.2)$$

Assuming that the increments in ε_{it} are independently and normally distributed, then as t → ∞, the term $\ln S_{io}$ will be small compared to $\ln S_{it}$, thus the limiting distribution of the logarithm of size ($\ln S_{it}$) is approximated by normal distribution; or equivalently the limiting distribution of size (S_{it}) is lognormal. This gives a testable hypothesis on the size distribution of firms at a point in time at which a deviation from lognormal distribution of size is considered as evidence against Gibrat's law. Equation (2.2) also indicates that firm growth is independent of initial size and only depends on the sum of idiosyncratic shocks. This will provide another testable argument on the relationship between current and initial size after reformulating:

$$\ln S_{it} = \beta_{i0} + \beta \ln S_{it-1} + u_{it} . \qquad (2.3)$$

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.

To formulate the growth-size relation, equation (2.3) can alternatively be written as:

$$\ln S_{it} - \ln S_{it-1} = \beta_{i0} + (\beta - 1)\ln S_{it-1} + u_{it} = \beta_{i0} + \beta_1 \ln S_{it-1} + u_{it} . \qquad (2.4)$$

In this case Gibrat's law is supported if the null $\beta_1 = (\beta - 1) = 0$ is not rejected, while $\beta_1 < 0$ implies that small firms grow faster than large firms, which is evidence against Gibrat's law.

Most early studies in developed countries reported close to lognormal distribution with some skewness to the right, which gives evidence in support of 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). Consequently, most recent studies tested directly the relation between growth and size and found a negative relationship contrary to Gibrat's law (Evans, 1987a,b; Hall, 1987; Kumar, 1985; Dunne and Hughes, 1994 among others).

The failure of Gibrat's law led to the development of firm growth literature in two directions: a rising interest in a rather new theory of firm growth and a justification of the failure in light of statistical problems.[4] Sutton (1997) reviews these developments extensively. The first direction of development moved the firm growth literature from a purely "stochastic process" to a more economically sensible "maximization problem", known as learning mechanism. This recent literature argues that systematic forces such as efficiency, investment difference (on 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 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 relates firm growth to firm specific efficiency difference.

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 given constant 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 previous market selection process.

On the other hand, the *active learning* model following Ericson and Pakes (1995) relates firm growth to investment in R&D, or in human or physical capital. The model assumes that the firm knows the current value of the parameter that determines the distributions of its profits, and that the parameter changes over time in response to the firm's own investments. As a result, in order to improve productivity (profitability), firms engage in competitive investment in uncertain but expectedly profitable innovations or cost reductions. Thus, those that are successful grow while the others

[4] 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.

shrink or die.[5] The implication of the active learning model is that as time passes, the dependence of growth on initial size disappears.

The other direction of research that sought statistical reasons for the failure of Gibrat's law tackles problems such as sample censoring, heterskedasticity, 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 the *articraft* of 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. Another 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.[6]

3. Data and Descriptive Analysis

The main data source of this study is 1996-2003 annual census data on manufacturing establishments collected by the Ethiopian Central Statistical Authority (CSA). In this annual census only establishments with 10 or more employees are surveyed.[7] This means that small firms are underrepresented, which might introduce some bias into the analysis. The original data constituted 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 percent of total firms, we deleted 579 observations and were left with 5,542 firm/year observations.[8]

Although, firm size could be measured in terms of sales, or of value added or fixed assets, it is here defined in terms of number of employees (i.e. the sum of both

[5] Some empirical studies have tested the active learning model by introducing investment variables such as physical investment, R&D investment, or human capital investment into the firm growth regressions (e.g. Hall, 1987; Mazumdar and Mazaheri, 2003).
[6] For a further discussion on these and other statistical concerns and proposed remedies, see the empirical section.
[7] In this analysis, establishment and firm are synonymous since most of the firms constitute a single plant.
[8] We have calculated the distribution of firms by ownership and location (not reported here). The share of the private sector in manufacturing in terms of proportion of firms is about 85 percent, but accounts for only 41 percent of employment in 2003. This means that the public sector is still the dominant employer, accounting for about 59 percent of total employment. Manufacturing firms are highly concentrated in the capital city Addis Ababa, although this share declined from 68 percent to 59 percent from 1996 to 2003.

permanent and temporary workers), unless otherwise mentioned. One obvious reason for this is that unlike other measures, employment is not affected by inflation. Employment generation is also more attractive from a policy perspective and makes comparison across studies easy.

3.1 Pattern of Firm Growth and Exit Rates

We next ask which types of firms in Ethiopian manufacturing are more likely to grow/decline and survive/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 two consecutive years.[9] Age is measured by the number of years since the firm's initial establishment. Exit or death on the other hand refers to firms that disappeared from the data before the end of sample period, and 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.

In assessing the pattern of growth and exit rates by size/age category, we need to take account of the nature of our data, which is described as annual census based panel data consisting of different categories such as firms surviving throughout the sample period, exiting firms and new entrants. Consequently, the classification according to initial size and age is not based on a single common year; rather we take each firm's first appearance in the data as a base for its size and age category following Dunne et al. (1989). Each firm is classified according to its employment size and age category in year t(t = 1996, 1997, …, 2002), and then the growth rate of employment is calculated from period t to t+1(t+1 = 1997, 1998, …, 2003) for each firm. The growth rate in each size/age class therefore represents average growth of net employment generation by each firm in the given category.

Table 1 presents firm growth and exit rates by size/age category. The overall growth rate of employment is positive with a 1.7 percent and a 2.6 percent annual average for all firms and only surviving firms respectively. Table 1a 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

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

negative. This shows that growth rate declines with size (for a given age) and with age (for a given size), but not monotonically.

Table 1 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	-	6.02
	(449)	(271)	(158)	(41)	(1)	(920)
2: 20 – 49	5.20	-2.24	-1.05	3.31	-	1.71
	(146)	(82)	(80)	(34)	(1)	(343)
3: 50 – 99	-2.87	-10.27	1.52	-1.21	-	-2.24
	(62)	(21)	(34)	(19)	(1)	(137)
4: 100 – 249	-0.39	-0.72	-4.50	-2.30	3.51	-2.09
	(23)	(17)	(34)	(31)	(5)	(110)
5: 250+	-1.37	-0.72	-2.73	-3.68	-1.88	-2.80
	(16)	(7)	(20)	(73)	(17)	(133)
Total	5.11	0.67	-0.03	-1.11	-0.53	1.72
	(696)	(398)	(326)	(198)	(25)	(1643)
b) Mean employment growth rate, only survivor firms						
1: 10 – 19	11.08	6.87	2.61	4.78	-	7.47
	(183)	(100)	(51)	(23)	(1)	(357)
2: 20 – 49	7.85	1.39	0.59	4.07	-	4.20
	(85)	(40)	(50)	(26)	(0)	(201)
3: 50 – 99	-1.94	-4.04	3.10	0.15	-	-0.44
	(40)	(15)	(18)	(13)	(1)	(87)
4: 100 – 249	0.36	-1.00	-2.88	-1.66	3.51	-1.27
	(15)	(12)	(26)	(27)	(5)	(85)
5: 250+	-0.32	-0.72	-2.73	-3.68	-1.88	-2.71
	(11)	(6)	(19)	(70)	(17)	(123)
Total	6.86	2.50	0.55	-0.80	-0.53	2.69
	(334)	(173)	(164)	(159)	(23)	(853)
c) Firm exit rate						
1: 10 – 19	59.24	63.10	67.72	43.90	0.00	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	0.00	36.50
4: 100 – 249	34.78	29.41	23.53	12.90	0.00	22.73
5: 250+	31.25	14.29	5.00	4.11	0.00	7.52
Total	52.01	56.53	49.69	19.70	8.00	48.08

Notes: the figures in parentheses in the upper two panels represent number of firms in each size/age category. The figures not in parentheses are in percentages, whereby the first two panels give average firm growth rate and the last panel exit rate at each size/age category. For definitions of surviving and exiting firms and growth rates, see Section 3.1 in the main text.

Table 1b gives the growth rate of only survived firms in the sample period. The growth pattern of the survived firms is broadly similar to the all firm patterns. 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 evidence 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 rate by size/age category in Table 1c. 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 the larger and the older firms, respectively.

3.2 Mobility of Firms, Matrix of Size Distribution

To investigate the ability of survived firms to move within different size categories, we constructed the mobility of firms across five size categories. Given the size category in the initial period, we calculated the percentage of survived firms that transit into other size classes at the end of the period. Table 2 presents the matrix of size transition for different period intervals of eight and five year durations.

Table 2a reports the mobility of firms in the eight 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 percent of the first size class (10-19), 17 percent of the second size class (20-49) and 21 percent of the third size class (50-99) moved up to their next higher size class. About 10 percent of the firms in the medium size 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 eight year period.

A large downsizing is observed, particularly among the medium size firms. For example, about 27 percent and 28 percent of the firms in the second and third size classes respectively moved down to their next lower size class from 1996 to 2003. Movement in both directions, scaling up and downsizing, is pronounced in these two size classes.[10] The general pattern of mobility in the five-year intervals, reported in Table 2b and 2c, is broadly similar with the full sample period pattern discussed above.

Table 2 Transition Matrix of Firms by Size Category

	Size categories					
	10-19	20-49	50 - 99	100-249	250+	Total
a) Transition of size by employment 1996 – 2003						
size 1996	size 2003					
1: 10 – 19	42 (0.60)	23 (0.33)	4 (0.06)	1 (0.01)	0 (0.00)	70
2: 20 – 49	17 (0.27)	33 (0.52)	11 (0.17)	3 (0.05)	0 (0.00)	64
3: 50 – 99	0 (0.00)	8 (0.28)	12 (0.41)	6 (0.21)	3 (0.10)	29
4: 100 – 249	0 (0.00)	1 (0.02)	5 (0.10)	37 (0.77)	5 (0.10)	48
5: 250+	0 (0.00)	2 (0.03)	1 (0.01)	12 (0.16)	60 (0.80)	75
Total	59	67	33	59	68	286
b) Transition of size by employment 1996 – 2001						
Size 1996	size 2001					
1: 10 – 19	50 (0.64)	23 (0.29)	5 (0.06)	0 (0.00)	0 (0.00)	78
2: 20 – 49	14 (0.19)	51 (0.69)	8 (0.11)	1 (0.01)	0 (0.00)	74
3: 50 – 99	1 (0.03)	4 (0.13)	16 (0.52)	8 (0.26)	2 (0.06)	31
4: 100 – 249	0 (0.00)	1 (0.02)	4 (0.08)	42 (0.86)	2 (0.04)	49
5: 250+	0 (0.00)	1 (0.01)	3 (0.04)	5 (0.07)	66 (0.88)	75
Total	65	80	36	56	70	307
c) Transition of size by employment 1998 – 2003						
Size 1998	size 2003					
1: 10 – 19	63 (0.74)	21 (0.25)	1 (0.01)	0 (0.00)	0 (0.00)	85
2: 20 – 49	16 (0.15)	76 (0.71)	13 (0.12)	2 (0.02)	0 (0.00)	107
3: 50 – 99	0 (0.00)	13 (0.26)	28 (0.56)	8 (0.16)	1 (0.02	50
4: 100 – 249	0 (0.00)	1 (0.02)	4 (0.07)	51 (0.84)	5 (0.08)	61
5: 250+	0 (0.00)	0 (0.00)	3 (0.04)	6 (0.08)	68 (0.88)	77
Total	79	111	49	67	74	380

Notes: 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.

Overall, the mobility across size class is limited with about 64 (184 firms) percent of the 286 survivor firms remaining in the same size classes from 1996 to 2003. When we consider the five-year transition, the percentage of firms that stayed in the same size

[10] 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 can not 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 cut-off point at 10 employees in our data, which means that movement to a lower class implies exit.

class rose to 73 percent and 75 percent for the periods 1996-2001 and 1998-2003 respectively. This is obvious given the difference in time interval of the transition; five years versus eight years. Our result is consistent with Biesebroeck (2005) who analyzed size matrices for manufacturing in nine African countries: about three-quarters and two-thirds of firms remain in their initial size category for an interval of 4 and 8 years, respectively.

3.3 Testing for Log-normality of Size Distribution

We next formally test Gibrat's law implied size distribution. The log-normality assumption in size is equivalent with an assumption of normality on the log of size. We therefore rely on testing the log of employment to show whether the size distribution is log-normal as predicted by Gibrat's law. If the log employment distribution deviates from normal then it is considered to be evidence against Gibrat's law. In testing the normality assumption in size distribution we follow two approaches: the graphical and the numerical methods.

Figure 1 Size distribution of firms by employment - selected years 1996 and 2003

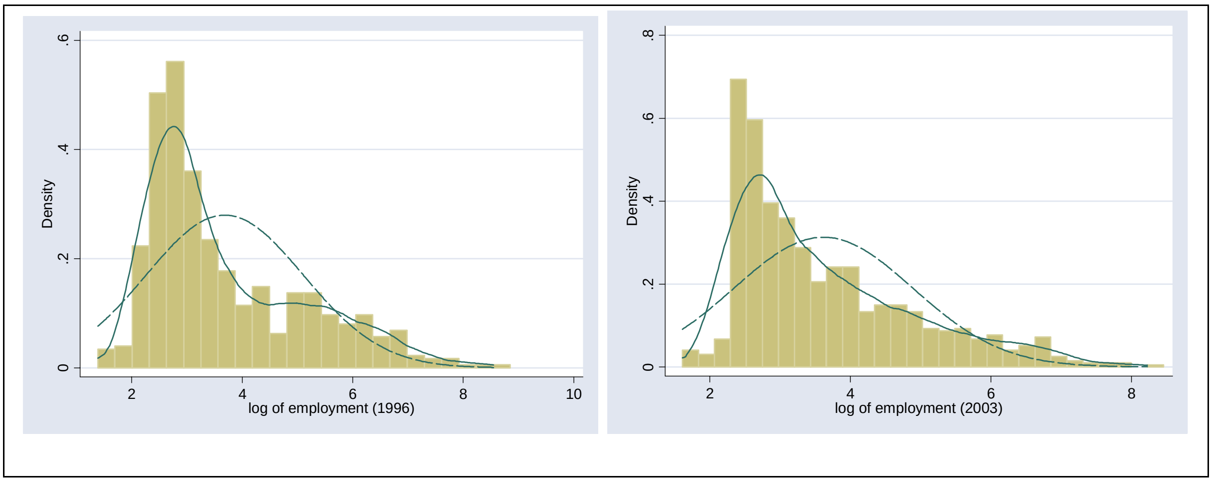

Figure 1 shows the histogram on the distribution of log employment for the selected years 1996 and 2003, along with a kernel density function and the normal distribution plot for comparison. The long dashed line and the unbroken line represent the normal and the kernel density curves respectively. As 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. The skewness of the size distribution is similar in both years suggesting that there is no significant change in distribution over the eight years. Hence, the graphical method provides a skewed size distribution and suggests evidence against Gibrat's law.

The visual judgment of normality from graphs is essentially subjective; thus formal methods to test normality are required. We used the Shapiro-Francia test for normality since it can accommodate a large number of observations, in contrast to the Shapiro-Wilk test.[11] Table 3 reports the test results. The normality assumption is rejected since the Shapiro-Francia statistic is statistically different from one in all years with p-value zero.

Table 3 Moments of size distribution and normality tests

		log employment				
Year	Number of firms	mean (s.d.)	median	Skewness (Prob. skw)	Kurtosis (Prob. kur)	Shapiro-Francia (Prob>z)
1996	561	3.68 (1.43)	3.14	1.04 (0.00)	3.21 (0.27)	0.89 (0.00)
1997	639	3.66 (1.37)	3.18	1.09 (0.00)	3.57 (0.01)	0.89 (0.00)
1998	660	3.64 (1.35)	3.14	1.1 (0.00)	3.48 (0.03)	0.89 (0.00)
1999	662	3.68 (1.38)	3.22	0.97 (0.00)	3.16 (0.35)	0.9 (0.00)
2000	663	3.71 (1.35)	3.3	0.97 (0.00)	3.21 (0.24)	0.91 (0.00)
2001	678	3.75 (1.32)	3.37	0.94 (0.00)	3.2 (0.26)	0.92 (0.00)
2002	826	3.59 (1.29)	3.14	1.1 (0.00)	3.5 (0.01)	0.89 (0.00)
2003	853	3.62 (1.27)	3.22	1.07 (0.00)	3.49 (0.01)	0.9 (0.00)
All	5542	3.66 (1.34)	3.22	1.04 (0.00)	3.37 (0.00)	0.9 (0.00)

Notes: the numbers in parentheses under the mean are standard errors, but the numbers in parentheses in the other columns represent p-values of the tests of the given statistics.

We further verified the normality hypothesis using additional versions of normality tests such as skewness and kurtosis (see Table 3). 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

[11] The Shapiro-Wilk test relies on the ratio of the best estimator of the variance to the usual corrected sum of squares estimator of the variance. The Shapiro-Francia is then an approximate test and is modification of the Shapiro-Wilk test for use with larger numbers of observations; i.e. up to 5,000 observations. The statistic should be positive and less than or equal to one. A Shapiro-Francia statistic different from one implies divergence from normality.

distribution has thicker tails. The skewness statistics in all years are above 0.94 and significantly different from zero. This shows that the log employment is skewed to the right and that the normality assumption is rejected. The Kurtosis test also rejects the normality assumption, particularly for the pooled data and half of the years. Combining all the test results, we conclude that Gibrat's law is once again rejected from our data. However, the test of log-normality of size distribution only provides indirect evidence that smaller firms grow faster than larger firms.

4. The Econometric Framework and Empirical Results

4.1 The Growth Model and Statistical Issues

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

$$(\ln S_t - \ln S_{t-1}) = \ln G(S_{t-1}, A_{t-1}, X_{t-1}) + u_t, \tag{4.1}$$

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 non-constant variance.

Several statistical issues arise in estimating equation (4.1). The first one is related to the functional form of $\ln G(A_{t-1}, S_{t-1}, X_{t-1})$. 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. Allowing for second-order expansion and considering a panel aspect of the data for firm i in year t equation (4.1) yields:

$$\begin{aligned} \ln S_{it} - \ln S_{it-1} &= a_0 + a_1 \ln S_{it-1} + a_2 (\ln S_{it-1})^2 + a_3 \ln A_{it-1} \\ &\quad + a_4 (\ln A_{it-1})^2 + a_5 (\ln S_{it-1} \times \ln A_{it-1}) + \sum_{j=1}^{k} b_j X_{it-1} + u_{it} \end{aligned} . \tag{4.2}$$

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,b).[12]

The most serious statistical problem in such a model is the effect of sample censoring due to exit. A failure is common among small firms, i.e. 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. Ignoring this problem will result in a downward bias estimate of the relationship between firm growth and size.

There are two popular methods in addressing the problem of sample selection. 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 (among others Hall, 1987; Evans, 1987a,b). The second method by Dunne, Roberts, and Samuelson (DRS, hereafter) (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 these two groups.

The first procedure is mathematically elegant, although there are some problems in applying it. First, it relies on distributional assumptions that the latent variable is normal, which is inappropriate. Second, separating sample selection, heteroskedasticity, and non-linearity 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 DRS (1989) approach, since this could help avoid the difficulties that arise from Tobit models (e.g. distributional assumptions and inter-correlation between sample censoring, heteroskedasticity, and non-linearity).[13] We estimate two separate growth models using OLS: one for only survived firms and the other for all

[12] 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 $E_A = \partial \ln S_{t+1} / \partial \ln A_t = g_A$.

[13] 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 doesn't affect the relationship between growth and size/age.

firms including exit firms in their pre-exit period.[14] The latter could help tackle the bias that arises from excluding exit firms in growth estimations. This bias is more for small firms.

However, one further concern in the growth models is that given that the small firms not only grow fast but also that their probability of exit is higher, exit should be explicitly considered as a -100 percent growth rate in the growth estimation. This is an important concern from a policy point of view, because the relevant question is not whether smaller/new firms have faster rates of employment growth than larger/older firms, but whether the growth rates of the smaller/new firms are large enough to compensate for their attrition rates (DRS, 1989). For this reason we estimate a third growth model that explicitly considers exit as a -100 percent growth rate. Assuming that if a firm exits its size equals zero, we define the growth rate of exiting firms in the period of exit to be equal to -1. In addition, since no other variable is observed after exit, we use the values of other covariates (for example size, age, and productivity) of the pre-exit year, i.e. the first lag. Then we apply OLS to estimate the growth rates on size, age, and other covariates for this extended data.

Assigning a -100 percent growth rate for the exit period is a bit strong given that exit might not necessarily imply shutdown. Due to the cut-off point in the survey at 10 employees, the firms that reduce their size to less than 10 workers are treated as having exited. This is of course more likely among small firms than large firms. Although this is a strong assumption, it might help clearing the empirical controversy in the growth-size relation. The reason is that if we still find an inverse relation between growth and size, this should be taken as strong evidence in support of the importance of small firms as a source of most new jobs, which is contrary to Gibrat's law.

The other 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, Haltiwanger, and Schuh (1996). Then this will be compared with results from an estimation of the growth model that relates average growth to current

[14] Our approach differs from the DRS (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.

size, in order to examine the effect of transitory fluctuation in the growth-size relationship, if any. Heteroskedasticity is another problem in the growth and size relations. We address the problem of non-constant variance by estimating heteroskedasticity-consistent standard error using the White (1982) method.

The next sub-sections provide empirical results based on different models of firm growth. The first sub-section presents the test of Gibrat's law where growth is regressed on size, age, and their second-order expansion. The second sub-section extends the basic model with productivity and other firm attributes, mainly testing the "passive learning mechanism".

4.2 Empirical Results of the Basic Growth Model

Table 4 reports the estimation and test results of the basic non-linear growth model for different specifications using OLS to the pooled data. The first column provides the estimation results of the firms that survived, while the second column gives the results of all firms, i.e. including those exiting firms in their pre-exit period. The third column reports the estimation result of all firms while considering exit as a growth rate of -100 percent. In all estimations we control for industry (17 industries at two-digit level) and year variations, but these are not reported here for brevity. The regular and heteroskedasticity-robust standard errors are reported under the coefficients in parentheses and square brackets, respectively.

The F-test for the null hypothesis that all second order size/age terms are jointly zero is significantly rejected in all models. Heteroskedasticity-consistent standard errors are reported in squared brackets, but relaxing the homoskedasticity assumption brings no important difference on the significance of the parameters. In all models both size and age take a negative sign at the first level and a positive at the second order, and all are highly significant. The interaction term is positive but insignificant. A negative coefficient of the first term and a positive coefficient of the squared term for both size and age imply that the relationship between growth and size/age is convex. This means that firm size/age affects growth negatively, but the negative effect diminishes with size/age. The turning point at which the negative effect of size on growth turns positive is a size of 372 employees for a given mean age, and the turning point for age is about 10.7 years old for a given mean size, based on the growth model in the first column in Table 4.

Table 4 Results of the basic growth models

Dependent variable annual employment growth	Current size/age: Only survived firms	All firms	All firms, but considering negative growth period	Mean size/age
$\ln(\text{size})_{t-1}$	-0.318***	-0.328***	-0.192***	-.410***
	(0.030)	(0.028)	(0.033)	(0.054)
	[0.055]	[0.047]	[0.050]	[0.185]**
$\ln(\text{age})_{t-1}$	-0.186***	-0.166***	-0.164***	-.218***
	(0.030)	(0.027)	(0.032)	(0.050)
	[0.038]	[0.034]	[0.040]	[0.087]**
$\ln(\text{size})_{t-1}^2$	0.026***	0.029***	0.018***	.047***
	(0.004)	(0.003)	(0.004)	(0.007)
	[0.007]	[0.006]	[0.006]	[0.026]**
$\ln(\text{age})_{t-1}^2$	0.036***	0.035***	0.039***	.063***
	(0.007)	(0.006)	(0.007)	(0.012)
	[0.008]	[0.007]	[0.008]	[0.0207]
$\ln(\text{size})_{t-1}*\ln(\text{age})_{t-1}$	0.004	0.001	0.000	-.021**
	(0.006)	(0.006)	(0.007)	(0.011)
	[0.007]	[0.006]	[0.007]	[0.024]**
Constant	0.937***	0.932***	0.414***	1.107***
	(0.073)	(0.065)	(0.076)	(0.118)
	[0.113]	[0.095]	[0.108]	[0.313]
N	3151	3896	4253	709
F-test ($S^2=A^2=S*A=0$)	F(3, 3123) =21.53***	F(3, 3868) = 50.7***	F(3, 4225) = 23.23***	F(3, 687) =26.45***

Notes: the dependent variable for the estimation on current size/age is current employment growth, whereas the dependent variable for the mean size/age estimation is mean growth of employment over the given period for each firm. Year and industry dummies are included in all estimations. The numbers in parentheses represent regular standard error and the numbers in square brackets represent heteroskedasticity-robust standard error. ***, **, and * represent one, five, and ten percent level of significance respectively.

When we compare the magnitude of the size/age coefficients among the different specifications, the first and the second columns are more or less identical. The maximum difference in the respective coefficients does not exceed 0.03 percentage points. The size coefficient of the third column that considers exit as a -100 percent growth rate is lower (in absolute value) compared to the first two columns. However, the basic growth-size relation remains unaffected.

In order to characterize the relationship between growth and size/age and make a comparison across different specifications tractable, we calculated the partial derivatives of size/age at different points: mean, median, 25th percentile, and 75th percentile (see Table 5). The partial derivative of size at these four points is found to be negative for all models, but in terms of magnitude the third column gives a lower partial derivative. We have also 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 85 to 89 percent of observations depending on the model. This shows that firm growth decreases with firm size for more than 85 percent of the sample. The fact that this negative relation is not affected by our explicit consideration of the growth rate of exiting firms including the -100 percent growth rate in the exit period, suggests that the inverse relationship between growth and size is not a result of articraft of sample censoring. Hence, our data provides strong evidence that smaller firms grow faster than larger firms, which is contrary to Gibrat's law.

Table 5 Effects of size and age, partial derivatives from the basic models

		Models			
		Current size/age			Mean size/age
Partial derivatives of size and age at		Only survived firms	All firms	All firms with negative growth period	Only survived firms
size	mean	-0.108	-0.100	-0.052	-0.100
	25th percentile	-0.167	-0.163	-0.091	-0.183
	median	-0.133	-0.127	-0.070	-0.146
	75th percentile	-0.057	-0.045	-0.019	-0.034
	negative fraction	0.89	0.881	0.852	
	positive fraction	0.11	0.119	0.148	
age	mean	0.006	0.012	0.027	0.011
	25th percentile	-0.059	-0.049	-0.039	-0.073
	median	0.006	0.013	0.030	0.024
	75th percentile	0.075	0.077	0.098	0.106
	negative fraction	0.466	0.469	0.433	
	positive fraction	0.534	0.531	0.567	

Notes: the fraction of negative and positive partial derivatives is calculated as the number of observations that lie below and above the turning point where the negative relation between growth and size/age turns positive, respectively.

The partial derivatives of age at the mean, median, and 75th percentile are positive, while the partial derivative of age at the 25th percentile is negative in all models. 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 in order to look at the extent of the negative growth-age relation. The partial derivatives of the growth function with respect to age were negative for about 43 and 47 percent of the observations depending on the model. This means that growth decreases with age for firms 10 years and younger, whereas growth increases with age for older firms, accounting for more than half of the sample. Hence, irrespective of the model the negative relation between growth and age predicted by the learning process affects only younger firms at the early stages of their life cycle (up to age 10).[15]

We next examine whether the negative growth-size/age relationships found in the current size/age regression above hold when we use mean size/age as explanatory variable following the suggestion by Davis et al. (1996). Comparing the results from both regressions is particularly important given the concern of transitory fluctuation or measurement error in size (see Table 4). The joint significant test of the second order terms is similarly rejected in the mean size/age specification, supporting the non-linear relationship. The coefficients of size/age are basically the same, except for some improvements in magnitude. Both the size and the age coefficients take a negative sign at the first level and a positive sign for the quadratic term, and all are significant, supporting the convex relationship between growth and size/age.

In order to make the comparison of the growth-size/age relationship between the specifications tractable, we have also calculated the partial derivative of size/age at different points using the OLS regression on mean size/age. As we can see in Table 5, the partial derivatives from the mean size/age specification are similar not only in sign, but also in magnitude with the current size/age specification. The partial derivative of size is negative at all points providing evidence that growth decreases with size. Hence, the previous finding that smaller firms grow faster than larger firms is not affected by the transitory fluctuations or measurement error in size. The growth-age relation in the mean size/age estimation is also similar to the previous finding.

4.3 Firm Growth, Productivity and other Firm Attributes

This sub-section introduces productivity and other firm attributes into the growth model. Productivity is included to examine the passive learning model prediction that more efficient firms grow/survive while the less efficient contract/exit. The productivity variable in this model is labor productivity measured by output per employee. The output is corrected for price movement using output price deflator at the two-digit level industrial classification, and labor is the sum of permanent and temporary workers.

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

The other additional variables included into the model are capital intensity, ownership, and location. Capital intensity is measured by the capital to labor ratio and might approximate differences in access to a wide range of resources such as capital. Location is also expected to capture differences among firms in access to better infrastructure and larger markets for skilled labor, raw materials, and outputs. 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. 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 those located in and around the capital city (as a large market area) might grow faster than their counterparts. Industry and year dummies are also included in all estimations, but are not reported.

Table 6 reports the OLS estimates of all three specifications: only survived firms, all firms, and the specification that considers exit to be growth rate of -100 percent. The relation between growth and size/age in this extended model is similar to that in the basic model, except for a small increase in magnitude. The convex relationship between growth and size/age is also unaffected in all models. The F-test for linear specification is rejected in favor of a non-linear relationship.

However, our main interest in this sub-section is how labor productivity and other additional firm attributes affect firm growth and survival. As we can see in Table 6, labor productivity is positively related to firm growth and significant in all models, suggesting that firms with higher labor productivity grow faster than firms with lower productive. 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.

Table 6 Results of the extended growth model on current size/age

Dependent variable annual employment growth	Only survived firms	All firms	All firms with negative growth period
$\ln(size)_{t-1}$	-0.386***	-0.380***	-0.255***
	(0.030)	(0.028)	(0.033)
	[0.055]	[0.046]	[0.049]
$\ln(age)_{t-1}$	-0.168***	-0.148***	-0.155***
	(0.030)	(0.027)	(0.031)
	[0.039]	[0.034]	[0.040]
$\ln(size)_{t-1}^2$	0.032***	0.032***	0.022***
	(0.004)	(0.003)	(0.004)
	[0.007]	[0.006]	[0.006]
$\ln(age)_{t-1}^2$	0.040***	0.039***	0.043***
	(0.007)	(0.006)	(0.007)
	[0.008]	[0.007]	[0.009]
$\ln(size)_{t-1}*\ln(age)_{t-1}$	-0.003	-0.005	-0.005
	(0.006)	(0.006)	(0.007)
	[0.008]	[0.007]	[0.008]
$(Y/L)_{t-1}$	0.040***	0.039***	0.046***
	(0.006)	(0.005)	(0.006)
	[0.007]	[0.006]	[0.007]
$(K/L)_{t-1}$	0.023***	0.021***	0.023***
	(0.004)	(0.003)	(0.004)
	[0.005]	[0.004]	[0.005]
Private	-0.124***	-0.134***	-0.133***
	(0.022)	(0.021)	(0.025)
	[0.033]	[0.030]	[0.031]
Location	0.042**	0.038***	0.037**
	(0.018)	(0.015)	(0.018)
	[0.019]	[0.016]	[0.019]
Constant	0.579***	0.539***	0.165*
	(0.093)	(0.082)	(0.096)
	[0.126]	[0.108]	[0.127]
# of observations	3087	3814	4162
F-test ($S^2=A^2=S*A=0$)	$F(3, 3055)$ = 50.14***	$F(3, 3782)$ = 56.09***	$F(3, 4130)$ = 27.43***

Notes: the dependent variable of all models is current employment growth. Year and industry dummies are included in all estimations. Note also that the numbers in parentheses represent regular standard error and the numbers in square brackets represent heteroskedasticity-robust standard error. ***, **, and * represent the one, five, and ten percent levels of significance respectively.

Capital intensity takes a positive and significant coefficient in all models. This means that firms with higher capital labor ratios grow faster than those with smaller capital labor ratios, mainly 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 less constraint of capital and other resources for the public firms in contrast to private firms.

5. Unobserved Heterogeneity and Firm Growth

Most previous studies testing Gibrat's law are based on cross-sectional regression 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, size growth can also be determined by other unobserved factors such as managerial ability. If these unobserved factors are correlated with the explanatory variables in the model, then the estimated coefficient from OLS is biased. 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 unobserved heterogeneity based on annual firm growth.

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

$$\Delta \ln S_{it} = c_i + \beta_1 \ln S_{it-1} + \gamma x_{it-1} + u_{it}, \qquad (5.1)$$

where c_i captures unobserved and time-constant firm specific effect, x_{it} other covariates, and u_{it} the pure error term. β_1 determines the relationship between growth and size. Gibrat's law predicts that $\beta_1=0$ while a correlation between size and growth ($\beta_1 \neq 0$) contradicts the law.

Estimating equation (5.1) by fixed effect could eliminate the unobserved heterogeneity effect, but would provide biased coefficients since this approach relies on the 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 provides substantial bias. The first differenced method is also inappropriate for the growth-size model since it relies on the stronger assumption that the explanatory variables should be sequentially exogenous. Instrument variable models that correct 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 difference of the explanatory variables and dependent variable as instruments in addition to the levels instruments.

We use the system GMM estimation (SYS-GMM hereafter) developed by Blundell and Bond (1998) to estimate equation (4.1), but for comparison we have also estimated fixed effect model.[16] In this section we consider only the extended growth model that introduces size and other covariates including year dummies. However, ownership, location, and industry dummies are excluded 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.

Table 7 reports the estimation and test results of the extended growth models correcting the effect of unobserved heterogeneity. In general, all models show a common pattern (except magnitude difference), particularly on the relation between growth and size. In all models, size takes a negative sign at the first level and a positive sign for the quadratic term, and both are significant. Productivity is positively related to growth; this is significant in all but one model. Capital intensity gives positive coefficient but is significant in only the FE model.

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 over-identification, the validity of instruments with only first lag and first and earlier lags (column II and III) is decisively rejected. The Sargan-Difference test between the instruments with first and earlier lags (model in column III) and second and earlier lags (model in column IV) is above the critical value even at the one percent level (i.e. chi-square 53.3 in contrast to 48.7 with degree of freedom 28), thus the validity of the first lags is once again rejected.[17] This shows that the RHS variables are endogenous to the model.

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[16] We have tested the appropriateness of the RE model against the FE model using the Hausman-test. We found evidence against the RE effect which means that the unobserved effect is correlated with the explanatory variables. We have also tested the pooled OLS against fixed effect. The F-test with the null that assumes no unobserved heterogeneity is rejected with $F_{(698, 2375)} = 5.04$ in favor of the FE model.

[17] If x_{it} are predetermined then the first and earlier lags of x_{it} are valid instruments whereas, if x_{it} are endogenous second and earlier lags of x_{it} are valid. The appropriateness of these instruments could be tested using the Sargan-Difference test, since the moment conditions specified under the weaker assumption (x_{it} are endogenous) are a strict subset of the set of moment conditions specified under the stronger assumptions (x_{it} are predetermined). Let S_0 denote the Sargan statistic obtained under the stronger assumption and S_1 denote the Sargan statistic obtained under the weaker assumption. If the

Table 7 Fixed effect and system GMM estimates of firm growth models

	Fixed Effect	SYS-GMM			
Dependent variable ΔSize	I	II	III	IV	V
$\ln(size)_{t-1}$	-0.889***	-1.23***	-1.186***	-0.965**	-0.553**
	(0.061)	(0.156)	(0.153)	(0.426)	(0.248)
$\ln(size)_{t-1}^2$	0.017**	0.12***	0.113***	0.10**	0.053**
	(0.008)	(0.018)	(0.018)	(0.04)	(0.0267)
$(Y/L)_{t-1}$	0.023***	0.030***	0.041***	0.130	0.090***
	(0.007)	(0.015)	(0.014)	(0.094)	(0.037)
$(K/L)_{t-1}$	0.020***	0.006	0.000	0.073	0.002
	(0.007)	(0.023)	(0.017)	(0.086)	(0.022)
Constant	2.75***	2.40***	2.272***	0.015	0.33**
	(0.167)	(0.426)	(0.395)	(1.12)	(0.55)
# of observations	3817	3817	3817	3817	3817
# of firms	1049	1049	1049	1049	1049
Tests					
Sargan-Hansen test		76.95	130.31	18.47	76.87
		[0.002]	(0.041)	[0.297]	[0.451]
m1		-7.69	-7.66	-5.53	-7.83
		[0.00]	(0.00)	[0.00]	[0.00]
m2		1.94	1.94	1.56	2.26
		[0.053]	(0.053)	[0.12]	[0.024]
Sargan-Difference test (b/n columns II and III) [a]		$\chi^2(28)=53.64$			
Sargan-Difference test (b/n columns III and V) [a]			$\chi^2(28)=53.36$		
Sargan-Difference test (b/n columns IV and V) [b]				$\chi^2(60)=58.4$	
Instruments					
for the differenced equation		t-1	t-1 & earlier	t-2	t-2 & earlier
for the level equation		t-1	t-1	t-2	t-2
Partial derivatives of size					
at mean	-0.758				-0.146
at median	-0.774				-0.196
at 25th percentile	-0.795				-0.259
at 75th percentile	-0.728				-0.050

Notes: the standard errors are robust finite sample corrected on two-step estimates derived from Windmeijer (2000). The Sargan-Hansen test of the over-identifying restriction is a minimized value of the two-step GMM criterion function and is robust to heterskedasticity 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) test respectively under the null of no serial correlation. The p-values of these different tests are reported in square brackets. The set of instruments in the respective columns constitute all RHS variables. ***, **, and * represent the one, five, and ten percent levels of significance respectively.

[a] The critical value for $\chi^2(28)$ is 37.9, 41.3, and 48.27 depending on a 10%, 5% and 1% significance level respectively.

[b] The critical value for $\chi^2(60)$ is 74.39, 79.08, and 88.37 depending on a 10%, 5% and 1% significance level respectively.

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simple difference $DS = S_0 - S_1$ is bigger than the critical value of chi-square with degree of freedom number of restrictions, then the x_{it} are endogenous; thus the first lags are not valid instruments.

Instruments with t-2 and t-2 and earlier lags passed the Hansen test of over-identification (columns IV and V in Table 7). We 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 which means that we are not able to reject the validity of earlier lags as additional instruments.[18] Moreover, the SYS-GMM with t-2 and earlier lags provide reasonable estimates of the parameters of interest. Thus, our preferred model is column V (i.e. the SYS-GMM model with t-2 and earlier lags).

In order to characterize the relation between growth and size we calculated the partial derivative of size at the mean, median, and the 25th and 75th percentiles (see the last rows in Table 7). The partial derivatives of size at all four points are found to be negative, which is consistent with the previous results in the pooled OLS estimations. This means that small firms grow faster than large firms even after controlling the effect of unobserved heterogeneity. When we compare the magnitude of the effect of size, the SYS-GMM provides comparable values to the pooled OLS whereas in the FE model the size effect is more pronounced. This is expected given that the FE effect provides biased estimates toward larger negative values.

To sum up this section, all models provide strong evidence that growth is negatively related with size. Hence, the previous finding that smaller firms grow faster than large firms is robust after controlling 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. Unlike the pooled estimation results, capital intensity is only significant in the FE estimation.

[18] The calculated Sargan-Difference statistics (i.e. is 58.4 with 60 degree of freedom) is less than the critical value of the chi-square (between 74.39 and 88.379 based on the one, five, and ten percent significance levels respectively, with degree of freedom 60).

6. Conclusions

We 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 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 sub-Saharan Africa 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 eight and five 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 size firms in the 1996-2003 period. As in most other developing countries, the sector is dominated by small firms mainly due to low urbanization, poor infrastructure, and a regulatory environment.

Second, firm growth decreases with size and this is not affected by the transitory fluctuations or measurement errors in size, corrections to sample censoring, or by controlling unobserved firm heterogeneity. Hence, our data provides 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 explicit consideration of growth rate of exiting firms to be -100 percent 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. Thus, small firms have an important role in the development process, and policies aiming at encouraging small firms might have a significant effect on 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 efficiency relative to others over time; thus growth is highest during this learning period. However, the relation between growth and age could take another form after some time, since age might capture effects that are more likely for older firms than for younger firms, such as better 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 continuous reallocation of resources from less efficient to more efficient firms takes place through growth differential.

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 growth difference among privately and publicly owned firms. Public firms grow faster than private firms. This might point to differences in access to finance and other network advantages between public and private firms. In other words, the private sector might have less access to these resources and therefore growth may be constrained.

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ESSAY III

Inactions and Spikes of Investment in Ethiopian Manufacturing Firms: Empirical Evidence on Irreversibility and Non-convexities

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Abstract

This paper provides empirical evidence on the effect of irreversibility and non-convexities in adjustment costs on firm investment decision based on 1996-2002 firm level data from the Ethiopian manufacturing. It relies on a rich census based panel data set that gives the advantage of disaggregating investment into different types of fixed assets. We document evidence of a large percentage of inaction intermitted with lumpy investment, which is consistent with irreversibility and fixed costs but not with the standard convex adjustment costs. The inaction is higher and investment lumpier for small firms. We complement the descriptive analysis with two econometric methods: a capital imbalance approach and a machine replacement model. With the capital imbalance approach we estimate the investment response of firms to their capital imbalance using a non-parametric Nadaraya-Watson kernel smoothing method. With the machinery replacement approach using a proportional hazard model that takes unobserved heterogeneity into account, we estimate the probability of an investment spike conditional on the length of the interval from the last investment spike.

Keywords: Investment, irreversibility, adjustment costs, African manufacturing

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1. Introduction

There has been a growing interest in modeling micro or firm level investment decisions in the last two decades. The introduction of adjustment costs following Eisner and Strotz (1963), with a main premise that capital cannot be adjusted without cost, has given way to a dynamic specification of investment models. The standard working assumption in this model is that the adjustment cost is strictly convex and differentiable. With a strictly convex adjustment cost assumption, the unit cost of investment rises as the scale of investment increases, making large and rapid investment extremely costly. Thus, this neoclassical model predicts that a profit-maximizing firm tends to spread or smooth its investment over time in order to avoid increasing marginal costs.

Recent developments in this literature have criticized the strictly convex adjustment cost assumption while emphasizing irreversibility and non-convex adjustment costs (Rothschild, 1971; Lucas, 1976; Abel, 1980; Dixit and Pyndick, 1994; Abel and Eberly, 1994). This departure from the neoclassical assumption has had a profound effect on our understanding of firm investment behavior. Unlike the incremental investment prediction of the strictly convex adjustment cost models, the irreversibility and fixed adjustment cost models suggest lumpy and intermittent investment. A number of empirical studies that rely on micro level data have also documented inaction and lumpiness of investment that are difficult to match with convex adjustment costs (Doms and Dunne, 1994; Bortello and Caballero, 1994; Abel and Eberly, 1996; Caballero, Engel, and Haltiwanger, 1995; Cooper, Haltiwanger, and Power, 1999; and Nilsen and Schiantarelli, 2003). Most of these empirical works are, however, based on the Longitudinal Research Database for the USA manufacturing sector.

Such empirical studies are scant in developing countries, and particularly in Sub-Saharan Africa (SSA hereafter). The only paper we are aware of that explicitly investigates irreversibility and adjustment cost in SSA is Bigsten et al. (2005), based on RPED survey data.[1] Nonetheless, we argue that if there are any gains from diverging from the neoclassical investment models to irreversibility and non-convex adjustment costs, they should become clear when looking at developing countries, and particularly at SSA for the following reasons.

[1] This study covers manufacturing in five SSA countries (Cameroon, Ghana, Kenya, Zambia, and Zimbabwe) and found that irreversibility has a significant impact on investment behavior, but no evidence of fixed costs. The paper is also part of Mans Söderbom's PhD thesis (2000).

First, the importance of irreversibility and non-convex adjustment costs on firm investment behavior should theoretically be pronounced in developing countries. This is due to limited and shallow secondary markets for capital goods, poor infrastructure, underdeveloped and often badly functioning financial markets, and a dense and uncertain regulatory environment often present in these economies (Tybout, 2000 and Bigsten et al., 2005). Second, the descriptive statistics in SSA manufacturing so far provide an exceptionally high range of inaction (zero investment episodes) in comparison to other regions.[2] Third, SSA manufacturing firms invest less, with a median investment rate equal to zero despite high profit rates. This is generally not explained by financial constraints (Gunning and Mengistae, 2001). We have detected this pattern (i.e. high profit rate but low investment rates) also in our data for the Ethiopian manufacturing firms (see Table A1).

Why is the inaction rate exceptionally high and investment generally low in these economies, despite the presence of high profit rates? This study tries to address this paradox by examining whether irreversibility and non-convex adjustment costs are important determinants of the investment decision using census based firm level data from the Ethiopian manufacturing. The data gives the advantage of disaggregating investment by type of fixed assets: machinery and equipment, non-residential building, vehicle, fixture, and furniture investment. This is very important in understanding the pattern of capital adjustment given the heterogeneous nature of the capital stock. It is the first of its kind for the Ethiopian manufacturing firms and believed to complement the few studies in other SSA countries.

In the descriptive analysis part, we document evidence of a large percentage of inaction intermitted with lumpy investment, which is consistent with irreversibility and fixed costs but not with the standard convex adjustment costs. In identifying the nature of adjustment costs and irreversibility, we applied two econometric methods: the capital imbalance approach following Caballero and Engel (1994) and the machine replacement model following Cooper, Haltiwanger, and Power (1999). The econometric models

[2] Bigsten et al. (2005) found that about 58 percent of the observations had zero investment episodes using firm level panel data on five African countries. We have also found similar results in our data for the Ethiopian manufacturing firms, where about 60 percent of the observations had zero investment. However, for the developed countries, such as the US, Spain, and Norway the percentage of inaction is only about 8 percent, 18 percent, and 21 percent, respectively (see Table A1 in the Appendix for a comparison).

provide evidence that supports the importance of irreversibility and non-convex adjustment costs, particularly for the disaggregated capital.

The next section gives the theoretical framework. Section 3 provides a descriptive analysis. Section 4 and 5 present econometric evidence based on the capital imbalance approach and machine replacement model respectively. The last section summarizes the findings.

2. Investment Pattern with Irreversibility and Non-Convex Costs: Theoretical framework

The prediction of the standard neoclassical investment model is at odds with the facts documented in different empirical studies. Consequently, the recent literature emphasizes the importance of irreversibility and non-convexity of adjustment costs including fixed and piecewise linear costs. Adjustment costs are fixed if the costs incurred are independent of the size of the investment. Rothschild (1971) shows the plausibility of fixed adjustment costs, e.g. costs of search and managerial decision, obtaining external financing, shutting down a plant while installing new equipment, and costs of information. The implication is that average costs decrease with the size of investment and a rational firm reduces its cost by bunching its investments into a few periods.[3]

The growing literature on irreversibility, started by Dixit and Pindyck (1994), provides another dimension that casts doubt on the standard assumption. Irreversibility arises from the difference between the purchasing and selling price of capital, mainly due to less developed markets for second-hand capital and the specificity of capital equipment. Irreversibility makes investments particularly sensitive to various forms of risks such as uncertainty regarding future product prices, input costs, tax structure, exchange rates, and regulatory activities.

There are two important effects of irreversibility on investment behavior. First, with a negative shock the firm cannot disinvest in the presence of irreversibility (total). Thus, gross investment is constrained to be non-negative even in the existence of excess

[3]The existence of piecewise-linear costs is also discussed in the literature. Here adjustment costs are assumed to be proportional to investment expenditure. In this case investments are predicted to be moderate (i.e. neither spread nor bunched) with a period of inaction.

capital. Second, there is a caution effect with regard to positive shocks. Firms do not respond immediately to small changes in fundamentals; rather, they tend to wait until certain thresholds are reached, which in turn extends the range of inaction. The range of inaction is particularly pronounced when irreversibility is combined with the presence of fixed costs.

We formally consider the optimization problem of a profit maximizing firm with a general structure of both variable and fixed adjustment cost in a competitive market:

$$\max \sum_{i \geq 0}^{\infty} \beta^t \left[\pi(A_t, K_t) - p_t I_t - C(I_t, K_t) \right], \tag{2.1}$$

where β_t is a discount factor, A_t profitability shocks, I_t investment, and K_t capital stock.

$\pi_t = Y_t(K_t, L_t) - w_t L_t$, is gross profit, and

$C(I_t, K_t) = VC(I_t, K_t) + FC(K_t)$ the sum of variable cost VC and fixed cost FC.

In this setup price of inputs is assumed to be competitive and exogenous to the firm, and labor is adjusted without cost. Capital stock follows the process $K_{t+1} = (1-\delta)K_t + I_t$. The fixed cost is assumed to be proportional to the installed capital stock (K). Thus, $FC(K_t) = 1(I_t > 0)\theta_F K_t$, where 1(.) is an indicator function equaling one if capital stock is adjusted and zero otherwise. θ_F is a constant parameter.

We assume complete irreversibility; that is, once purchased, capital cannot be sold.[4] In each period the firm faces two choices: to adjust or not to adjust its capital stock (a discrete choice). With zero investment, firms continue to get a flow of profit on the given capacity, whereas with positive investment, firms incur some additional costs (including the opportunity cost of investing rather than waiting) and a flow of revenue with the additional capacity. Thus, to make a decision the firm needs to compare the value function with capital adjustment and the value function with no adjustment.

The Bellman equation to solve the maximization problem is:

$$V(A_t, K_t) = \left[\max V^i(A_t, K_t), \max_{I_t} V^a(A_t, K_t, I_t) \right], \tag{2.2}$$

[4] This assumption is not restrictive given the absence of a second hand market for capital in Ethiopia. Our data set shows that only about one percent of the firms are able to sell more than 10 percent of their capital. An extension of the model including partial irreversibility can be found in Caballero (1997), Cooper, and Haltiwanger (2000), and others.

where V^i is the value function with no adjustment (inaction) and V^a the value function in the case of adjustment (action).

The dynamic problem of these two cases could be written as follows:

$$V^i(A_t, K_t) = \prod(A_t, K_t) + \beta^t E_{A_{t+1}|A_t} V[A_{t+1}, (1-\delta)K_t] \tag{2.3}$$

$$V^a(A_t, K_t, I_t) = \max_{I_t} \prod(A_t, K_t)\lambda - p_t I_t - C(A_t, K_t, I_t) + \beta^t E_{A_{t+1}|A_t} V[A_{t+1}, K_{t+1}], \tag{2.4}$$

where $A_{t+1}|A_t$ represents conditional expectation and (1- λ) captures the profit forgone due to production disruption and is independent of investment scale.

If we assume no fixed costs, the value function could be solved since it is continuous and concave. However, with the presence of fixed costs the value function is non-concave. The first order condition does not guarantee a global maximization, therefore the solution becomes complex.

Let s_t denote the vector of state variables (including profitability shocks and firm characteristics) and θ represent structural parameters (scale of adjustment cost and irreversibility). Then following Sánchez-Mangas (2002) and its references, the optimal investment decision rule with the non-concave value function could be written as:

$$i(s_t, \theta) = \begin{cases} i^*(s_t, \theta) & \text{if} \quad i^*(s_t, \theta) > 0 \ \text{ and } \ \gamma(s_t, \theta) > 0 \\ 0 & \text{othewise,} \end{cases} \tag{2.5}$$

where $i^*(s_t, \theta)$ is the optimal solution characterized by

$$\tilde{\pi}_i(s, i^*(s,\theta), \theta) + \beta EV_i(s, i^*(s,\theta), \theta) = 0 \tag{2.6}$$

$$\text{with } \tilde{\pi}_i = \frac{\partial \pi}{\partial i} \text{ and } EV_i = \frac{\partial EV}{\partial i}, \qquad \text{and}$$

$$\gamma(s_t, \theta) = \tilde{\pi}(s, i^*(s,\theta), \theta) - FC(s,\theta) - \pi(s, 0, \theta) + \beta\left[EV(s, i^*(s,\theta), \theta) - EV(s, 0, \theta)\right]. \tag{2.7}$$

Equation (2.6) provides the optimal condition for an internal solution, and equation (2.7) shows the relative gain from adjusting. If equation (2.6) is maximized for negative values, then we have a corner solution equal to zero due to complete irreversibility constraints. The firm will make no adjustment leading to a range of inaction. When equation (2.6) is maximized for positive values, then the interior solution will be optimal.

However, an internal solution to equation (2.6) might not guarantee positive investment. Even if equation (2.6) is maximized for positive values, in the presence of fixed costs the value obtained with adjustment could be lower than the value obtained with no adjustment (i.e. $\gamma(s_t, \theta) \leq 0$ in equation 2.7). For instance, if K is near the level that maximizes equation (2.3), then the net gain from adjusting will be negative since FC are positive even for small adjustments. Then the optimal decision will be inaction. This implies that there should be a certain threshold where the gain from adjusting should be high enough to lead the firm to make an investment. Thus, the combination of irreversibility and fixed costs of adjustment produces a large range of inaction. Positive investment will only take place when both equations are positive (i.e. $i^*(s_t, \theta) \succ 0$ and $\gamma(s_t, \theta) \succ 0$).

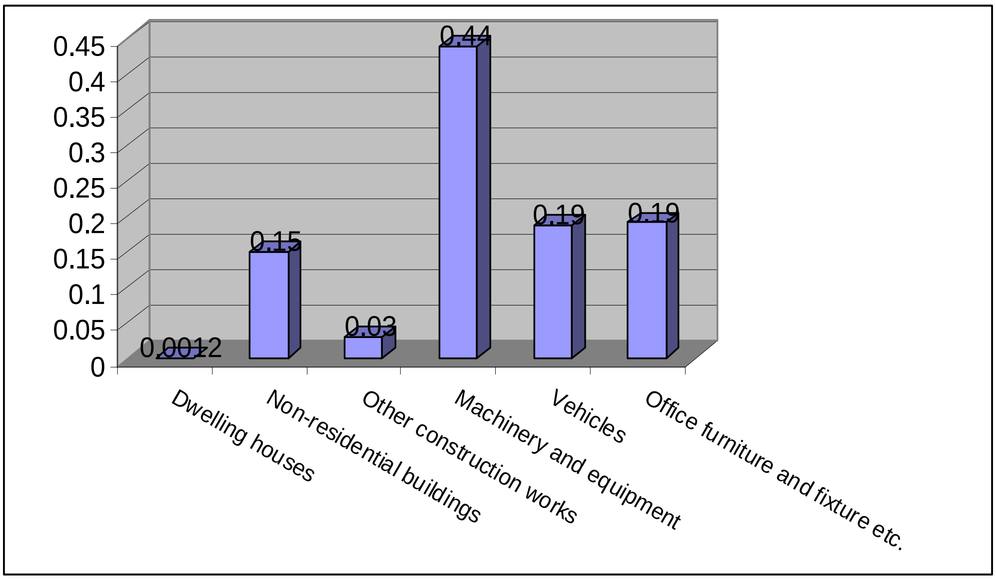
3. The Data and Descriptive Analysis

The data basis of this study is the establishment level industrial census on all Ethiopian manufacturing firms with 10 or more employees, collected annually by the Ethiopian Central Statistical Authority (CSA). The original data consists of 5,182 firm/year observations from 1996 to 2002. Mainly due to our imposition of a requirement on each firm to be observed for at least four consecutive years for analytical purposes, the sample of this study contains only 478 firms with 2,845 firm/year observations. This means that the sample covers about 55 percent of the original data in terms of the number of firms, but in terms of permanent employment and investment expenditure on total fixed assets it accounts for 78 percent and 76 percent, respectively.

The original data contains capital at the beginning of the year, investment, sold assets, depreciation, and end year capital by firm and type of fixed assets. However, to avoid inconsistency we take only the beginning year capital stock for the first year that the firm is observed in the data and subsequently construct the capital stock for each category of fixed assets using a perpetual inventory method (for a further explanation on the construction of the variables, see data appendix). Throughout this study, investment refers to expenditure on fixed assets minus sales of fixed assets, i.e. net investment. Investment rate is then defined as the ratio of investment expenditure (net of sold assets) to end year capital stock.

Figure 1 gives investment expenditure distribution by type of fixed asset. On average, machinery and equipment (M&E henceforth) investment accounts for about 44 percent of total investment in fixed assets. Vehicle purchases and furniture each accounts for about 19 percent of total fixed asset investment, followed by non-residential buildings at about 15 percent. This means that the investment outside machinery and equipment (non-machinery fixed assets, NMFA henceforth) accounts for more than half of the total fixed asset (TFA henceforth) investment. Hence, our investment analysis should also take into account the NMFA component of investment.

Figure 1: Investment share by type of fixed assets



Next we look at the distribution of investment rates to examine the nature of non-smoothness of the investment pattern. Table 1 provides the distribution of the investment rates and shares of investment outlay in total fixed assets and its different categories. The percentage of observations with zero investment episodes is about 59 for M&E and 55 for NMFA. This means that more than half of the firms in an average year refrain from investing. The inaction rate for Ethiopia is exceptionally high in comparison to the developed world, but similar to findings in other SSA countries (see Table A1). If we aggregate the investment expenditure to total fixed assets (TFA), zero investment episodes account for about 46 percent of all observations. This shows that aggregating investment on heterogeneous capital will underestimate the nature of intermittency of investment, though the inaction rate is still high.

Table 1 Investment rate and share of investment distribution

Investment rate	Machinery and equipment (M&E)		Non-machinery fixed assets (NMFA)		Total fixed assets (TFA)	
	frequency	share	frequency	share	frequency	share
<0	2.25	-3.21	1.99	-3.69	2.07	-2.78
=0	58.6	0	54.8	0	45.56	0
0<I/K<0.05	15.22	6.19	16.98	5.65	20.49	5.87
0.05=<I/K<0.1	5.45	7.72	5.62	8.35	8.96	15.16
0.1=<I/K<0.2	6.15	14.99	6.61	15.19	8.26	17.5
0.2=<I/K<0.3	3.83	11.86	4.32	16.87	5.41	15.93
I/K>=0.3	8.51	62.44	9.67	57.64	9.24	48.32
Total	100	100	100	100	100	100

Table 1 also presents the frequency of observations ever sells fixed assets, showing the extent of second-hand capital market. Only about two percent of the observations involve selling any type of fixed assets. Moreover, the percentage of observations of firms selling 10 percent or more of their fixed asset is negligible, accounting for only one percent. The high frequency of inaction and only a few negative investment rates is consistent with the existence of fixed adjustment costs and irreversibility, but not with convex adjustment costs.

We further assessed the investment rates and the frequency of zero investment episodes by size (not reported here). Small firms are defined as having fewer than 100 permanent employees, while large firms have 100 or more permanent employees. The proportion of observations with zero investment episodes among small firms in M&E is more than double (about 70 percent) that of large firms (about 27 percent). The difference is even greater (more than three times) for TFA with an inaction rate 56.6 and 14.5 percent for small and large firms respectively. This shows that inaction is higher among small firms.

But how lumpy is investment when it takes place? Table 1 also reports the distribution of positive investment rates. The proportion of large investment observations (investment rate of 20 or more percent) is only 12-14.5 percent, depending on the type of fixed asset. Observations of positive investment of less than 10 percent of capital, on the other hand, accounts for 21-29 percent, depending on the type of fixed assets. Considering only observations with positive investment, the frequency of small investments accounts for above 50 percent. The high frequency of small investments is justified on the grounds that adjustment costs are negligible for small investments that are largely replacement investments. The fixed cost becomes important only for expansion investment (Nilsen and Schiantarelli, 2003).

An interesting outcome emerges when we compare the percent of observations involved and shares of investment outlay by certain intervals. For instance, the proportion of observations with investment rates of 20 or more percent is 12 percent and 14 percent for M&E and NMFA respectively, but their shares of total investment outlay are above 73 percent. This means that no more than 15 percent of the observations account for about three-quarters of total investment outlay, which provides some evidence of investment lumpiness.

However, this only tells us that on average there are few observations of large investments, but nothing about the within firm investment distribution and pattern over time. In a cross-sectional distribution of investment we can't determine whether investment spikes are important for individual firms (Bigsten et al., 2005). Hence, it is vital to assess the episodes of investment of each firm over the years to further understand how lumpy individual firm investments are. Following Doms and Dunne (1998), we ranked investment rates of each firm over time from highest (1) to lowest (7). Then we computed the average investment rates for each rank and the share of investment of that rank of total investment outlay. In order to have a clear understanding of the process, we concentrated on firms that stay in the data the full sample period. This balanced panel consists of 247 firms with 1,729 observations.

Table 2 gives the rankings and shares of investment rates by types of fixed assets. The average investment rate for the TFA in the highest rank (rank 1) is about 30 percent, which is four times the average investment rate and more than double the second highest investment rate rank. The first rank accounts for about 45 percent of the total fixed investments over the seven year period, which is double that of the second rank. This shows that investments are concentrated in a few years.

The lumpiness is also marked when we look at the disaggregated capital M&E and NMFA investments. The average investment rate of the first rank is 30 percent for M&E and 35 for NMFA, which is still more than double that of their second rank. The first rank accounts for 56 percent and 46 percent of the total investment expenditure over the seven years in M&E and NMFA respectively. This means that 56 percent and

46 percent of the total investment of an average firm in seven year period takes place in a single year for M&E and NMFA respectively. If we add the first two ranks, the same shares rise to about 79 percent and 70 percent respectively. This shows that investments are lumpy also at the firm level. It also reveals the importance of lumpy investments at firm level for aggregate investment.

Table 2 Ranking of investment episodes and contribution to aggregate by size

Rank		M&E			NMFA			TFA		
		small	large	All	small	large	All	small	large	All
1 (Highest)	Mean (I/K)	0.26	0.35	0.30	0.3	0.43	0.35	0.29	0.32	0.3
	share	48.76	57.49	55.9	74.97	41.73	46.04	53.42	43.03	44.91
2	Mean (I/K)	0.08	0.19	0.13	0.1	0.21	0.14	0.11	0.18	0.14
	share	26.27	22.55	23.22	18.94	24.18	23.51	24.22	21.63	22.1
3	Mean (I/K)	0.03	0.09	0.06	0.05	0.13	0.08	0.05	0.13	0.08
	share	13.98	9.86	10.61	8.2	19.17	17.75	16.82	14.54	14.95
4	Mean (I/K)	0.01	0.05	0.03	0.02	0.07	0.04	0.02	0.09	0.05
	share	4.92	8.16	7.57	5.22	8.58	8.14	3.07	10.95	9.53
5	Mean (I/K)	0.01	0.03	0.01	0.01	0.04	0.02	0.01	0.06	0.03
	share	4.54	3.78	3.92	3.27	6.3	5.91	4.51	7.06	6.6
6	Mean (I/K)	0	0.01	0.01	0.01	0.02	0.01	0	0.03	0.01
	share	1.29	1.82	1.72	1.47	2.76	2.59	1.02	4.67	4.01
7 (Lowest)	Mean (I/K)	-0.02	-0.02	-0.02	-0.03	-0.02	-0.02	-0.03	0	-0.02
	share	0.22	-3.65	-2.95	-12.1	-2.72	-3.93	-3.06	-1.87	-2.09
average	Mean (I/K)	0.05	0.1	0.07	0.06	0.13	0.09	0.06	0.12	0.08
Number of observations		1087	642	1729	1087	642	1729	1087	642	1729

Notes: Small firms are defined as having fewer than 100 permanent employees, while large firms have 100 or more permanent employees.

Our result is consistent with previous findings considering the difference in the length of the period. Using U.S. data, Doms and Dunne (1998) found about 50 percent of total investment over 16 years is made in the three highest ranks. Nilsen and Schiantarelli (2003) documented that the three highest ranks account for about 53 percent of total investment outlay in machinery and equipment over 14 years in Norwegian manufacturing. Bigsten et al. (2005) reported that the first rank accounts for 50 percent of the investment outlay over five years for five African countries.

We have also compared the lumpiness of investment by size (see Table 2). The first rank average investment rate for the small firms is about three times greater than that of the second rank, while for the larger firms the rate of the first rank is not more than twice that of the second rank. This shows that investment is lumpier for small firms. Combining this with our previous finding that inaction is also higher for small firms suggests that the intermittent nature of investment is pronounced in small firms. Nilsen and Schiantarelli (2003) and Bigsten et al. (2005) found a similar result based on their investment rank comparison across size. They argue that small firms are more affected by indivisibilities since these set lower limits on investments that leave firms with a choice of either a large investment or zero investment.

To sum up the descriptive analysis, we documented that the second-hand market for M&E is almost non-existent. M&E were sold in only two percent of the observations, and only one percent of the observations showed sales of at least 10 percent of the firm M&E capital. The proportion with zero investment episodes is very large, accounting for about half of the observations. When investment takes place it is found to be lumpy and concentrated to few observations and few periods. The intermittent nature of investment is pronounced for small firms. The existence of lumpy and intermittent investment is consistent with irreversibility and fixed adjustment costs, but not with convex adjustment costs. However, this is also consistent with other explanations; for example lumpy investments may be indicative of large shocks as well. The descriptive analysis should therefore be complemented by more structured econometric evidence. This is the task of the next two chapters.

4. The Capital Imbalance Approach: A non-parametric analysis

The capital imbalance approach initiated by Caballero and Engel (1994), the CE model hereafter, explains how firms adjust their capital stock to deviations in their desired capital from their actual capital stock.[5] This could be characterized in terms of the two value functions in the Bellman equation (2.2), but with different arguments for $V^i(x, k^*)$ and $V^a(x, k^*)$, where x and k^* denote the capital imbalance and desired capital respectively. Since firms do not adjust continuously and respond differently to

[5] The capital imbalance approach was employed by among others, Caballero et al. (1995) using data on U.S. manufacturing firms, Goolsbee and Gross (1997) using U.S. airline industry data, and Bigsten et al. (2005) on five African countries.

similar imbalance x over time and across firms, the response could better be captured by a probabilistic rather than a deterministic adjustment rule. Empirically this can be described by a state dependent hazard function, i.e. the probability of a firm adjusts its capital given the absolute value of the deviation of desired capital from its actual capital stock (Caballero, 1997).[6]

This state-dependent hazard function takes different shapes and provides information about the nature of adjustment costs. The implied shape of different adjustment costs in this framework adopted from Goolsbee and Gross (1997) is given in Figure A1. Linearly increasing hazard is consistent with convex adjustment costs. Piecewise linear adjustment costs also predict a linear relationship, but with a certain range of inaction. Irreversibility generates a large flat portion (range of inaction). When large deviations of actual from desired capital lead to proportionately larger changes in investment than small deviations, then the hazard function increases non-linearly, consistent with the presence of fixed adjustment costs.

The CE model involves a two-step estimation: constructing mandated investment and then estimating non-parametrically the firm's actual investment response to its mandated investment.[7] First, we construct the mandated investment index, x, that measures the deviation of desired from actual (natural log of) capital stock at the plant level. A positive x reflects capital shortage, while negative values reflect excess capital.

$$x_{it} \equiv \widetilde{k}_{it} - k_{it-1}, \qquad (4.1)$$

where $\widetilde{k}_{it}$ and k_{it-1} represent the natural log of desired and actual capital, respectively, in plant i at time t (before adjustment).

Deriving the desired capital stock is one important challenge in this formulation. We assume that the desired capital stock is proportional to the stock of frictionless capital, k^*_{it}.

$$\widetilde{k}_{it} = k^*_{it} + d_i, \qquad (4.2)$$

[6] Unlike the machinery replacement model where the probability of adjusting depends on age of capital (time since last investment), this adjustment hazard is state-dependent, i.e. a state of capital imbalance (Caballero and Engel, 1993).

[7] Caballero et al. (1995) extensively discuss the theory and measurement of mandated investment. This section relies heavily on their model specification. A detailed derivation of the model can be obtained from their paper.

where d_i is a plant specific constant, the desired capital ($\tilde{k}_{it}$) refers to the stock of capital the firm would hold if adjustments costs were momentarily removed, and frictionless capital (k_{it}^*) refers to the stock of capital that the firm would hold if it never faced adjustment costs.

The frictionless capital can therefore be determined from a neoclassical expression that formulates capital as a function of output and cost of capital, assuming perfect competition, constant returns to scale, and no adjustment costs.

$$k_{it}^* = y_{it} - c_{it}\,, \tag{4.3}$$

where y_{it} and c_{it} represent the natural logs of the value of output and cost of capital for firm i at time t respectively.

Substituting equation (4.3) into equation (4.2) yields the desired capital, as a function of output, cost of capital and firm specific effect:

$$\tilde{k}_{it} = y_{it} - c_{it} + d_i\,. \tag{4.4}$$

There are two specification issues at this moment. First, since the desired capital is not observable, it needs to be approximated by another variable. The long-run desired capital can be derived from a regression of actual capital on a constant, output, and cost of capital.[8] The second concern arises from the lack of measure of cost of capital in our data set. One way to deal with this problem is to assume that the user cost of capital changes slowly and can be eliminated using a fixed effect model in the panel data setup.[9] Hence, the fitted value of the regression of actual capital on output in a fixed effect model provides a measure of desired capital. Then the mandated investment rate can be constructed by subtracting the beginning year capital from the derived desired capital, ($\tilde{k}_{it}$ - k_{it-1}).

The second step involves regressing the actual investment rate, I_{it}/K_{it-1}, on the mandated investment rate ($\tilde{k}_{it}$ - k_{it-1}):

$$I_{it}/K_{it-1} = f(\tilde{k}_{it} - \mathrm{k}_{\mathrm{it-1}}) + \lambda_{\mathrm{it}}\ . \tag{4.5}$$

[8] Bertola and Caballero (1994) discuss on this point in detail. The firm specific constant that approximates the deviation of actual from estimated frictionless capital stock, and therefore desired capital stock is assumed to be stationary. All the observable series are also expected to be co-integrated, because a large gap between actual capital and frictionless capital cannot be sustained infinitely. In the face of co-integrated series, the OLS estimate is consistent and we can reveal the desired capital from the fitted value of this specification.

[9] Bigsten et al. (2005) follow the same approach.

Following Goolsbee and Gross (1997), we estimated equation (4.5) non-parametrically using the Nadaraya-Watson kernel smoothing method.[10] Figures 2a and 2b present the shape of the adjustment cost from the kernel regression for investment on M&E and TFA respectively. In both figures a large flat curve, in the range of negative mandated investment and a certain distance of positive mandated investment, is followed by a positive and steep curve. This larger range of inaction followed by a steeper curve suggests an impact of irreversibility and a broad category of non-convexities. However, this might be consistent with both piecewise linear costs and fixed adjustment costs. Further examination is therefore required regarding whether the piecewise linear or the fixed cost predicts the investment behavior better.

Figure 2a Kernel estimation of mandated investment (machinery and equipment)

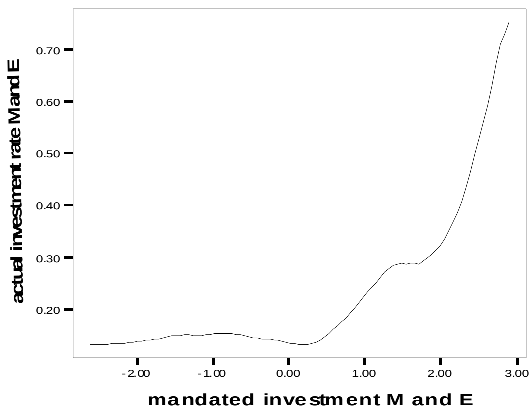
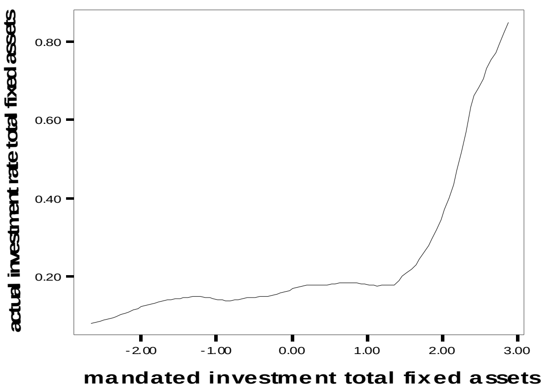


Figure 2b Kernel estimation of mandated investment (total fixed assets)



[10] The regression uses the triangular kernel and the bandwidth is calculated with ($b = 2.347 * \sigma * n^{-.2}$), where sigma is the standard deviation of the independent variable and n is the number of observations. To correct for outliers we removed observations in the bottom and top 5 percentiles for the variable mandated investment.

We use a parametric method to verify the existence of a non-linear relationship between actual and mandated investment rates. A non-linear relationship implies that the average response to larger disequilibria is proportionally larger than the response to small disequilibria, supporting fixed adjustment costs rather than piecewise linear costs. In this context, we estimate the actual investment rate over mandated investment and squared mandated investment for all observations and observations with positive investment separately. A significant coefficient of the squared mandated investment is considered to be evidence of fixed adjustment costs. We use a simple OLS method pooling the observations while controlling year variation.

Table 3 reports the estimation results. The first two columns give estimation results for both M&E and TFA, but conditional on positive investments, while the last two columns provide the estimation results for all observations including those with zero investments. In all estimations the coefficient of the squared mandated investment is positive and highly significant. The positive and significant squared mandated investment in both types of assets provides strong evidence of a non-linear relationship between actual and mandated investment rates. This is consistent with the fixed adjustment cost prediction.

Table 3 Test of non-linearity of investment response to capital imbalance

	Observations with only positive investment		All observations	
	M&E	TFA	M&E	TFA
x_{it}	0.310***	0.180***	0.064***	0.071***
	(0.0485)	(0.043)	(0.024)	(0.027)
x_{it}^2	0.073***	0.033*	0.044***	0.042**
	(0.021)	(0.020)	(0.015)	(0.019)
Year 1998	0.098	-.0259	-0.006	-0.038
	(0.253)	(0.215)	(0.115)	(0.126)
Year 1999	-0.248	.1757	-0.128	0.084
	((0.240)	(0.208)	(0.111)	(0.122)
Year 2000	-0.321	-.147	-0.174*	-0.116
	(0.243)	(0.210)	(0.111)	(0.121)
Year 2001	-.181	-.060	-0.166**	-0.074
	(0.247)	(0.210)	(0.112)	(0.122)
Year 2002	-.425	-.176	-0.234***	-0.139
	(0.250)	(0.214)	(0.115)	(0.125)
Constant	0.639***	0.348***	0.251***	0.180*
	(0.187)	(0.152)	(0.089)	(0.096)
# of observations	920	1228	2097	2162
F - test	F(2, 912) =7.16	F(7, 1220)= 3.34	F(7, 2089)= 3.56	F(7, 2154) = 2.45
	Prob>F = 0.00	prob>F = 0.002	Prob >F = 0.0008	Prob > F = 0.017

Notes: the dependent variable is investment rate, and x_{it} stands for mandated investment. Values in parentheses are standard errors. ***, **, and * show significance at the 1%, 5% and 10% level respectively.

We next summarize the implications of the findings from the CE model. The large portion of inaction, as implied by the flat curve, shows that firms do not reduce their capital stock even if the desired capital is much smaller than the actual capital. This is a typical case of irreversibility. The strong non-linear relationship between actual investment and mandated investment gives evidence of non-convexities in the adjustment cost, but not of convex adjustment cost. Specifically, this is consistent with the fixed cost prediction, where large deviations of actual from desired capital lead to proportionately larger investment than small deviations. The existence of a threshold in capital imbalance implies that firms tend to bunch their investments in few periods.

5. The Machine Replacement Model: The hazard of investment spikes

The machine replacement model developed by Cooper et al. (1999), the CHP model hereafter, analyzes the probability of a second investment episode conditional on the length of the last investment episode.[11] It assumes the productivity of capital, and therefore the profit function is influenced by the age of capital and the productivity shock. The solution to the Bellman equation (2.2) can also be characterized by the hazard function θ(k, A); the probability of investment given the age of the current capital stock (k) and productivity shock (A). The timing of an investment response to a productivity shock depends on the nature of the adjustment costs (λ and $C(A_t, K_t, I_t)$ in equation 2.4) and on the persistence of the shocks.

With fixed adjustment costs, the model predicts that the hazard of investing increases with the time since the last investment, thus the hazard is upward sloping. This is because in the presence of fixed costs, the productivity gains from an additional investment in a period soon after the first investment are small. In the face of serially correlated shocks with convex costs, the firm level investment will be positively correlated; therefore the hazard is downward sloping. On the other hand, with serially uncorrelated shocks and no adjustment costs, the hazard should be flat.

In this section we introduce the CHP method to examine if the probability of an investment spike increases with the time since the last investment spike using a discrete duration model. Let T_i be the length of firm i's spell between two investment spikes.

[11] Cooper, Haltiwanger, and Power (1999); Nilsen and Schiantarelli (2003); and Bigsten et al. (2005) among others employed the machine replacement model in identifying the shape of adjustment costs.

The hazard, h_{it}, of exiting from the spell (i.e. the probability of an investment spike) of firm i at time t can be stated as follows:

$$h_{it} = \lim_{dt \to 0^+} \frac{prob(t + dt \succ T_i \geq t \mid T_i \geq t, x_{it})}{dt}, \tag{5.1}$$

where x_{it} is a vector of additional conditioning variables.

Parameterizing the hazard function using a proportional hazard form gives:

$$h_{it} = h_0 \exp(x_i(t)'\beta), \tag{5.2}$$

where h_o is the baseline hazard.

The probability that a spell of zero investment lasts until period t+1, given that it has lasted until period t in a discrete time can be written as:

$$p\left[T_i \geq t+1 \mid T_i \geq t, x_{it}\right] = \exp\left[-\exp\{(x_i(t)'\beta) + \gamma(t)\}\right], \tag{5.3}$$

where $\gamma(t)$ a baseline hazard representing duration in discrete time.

The above equation gives the survival function, but could be easily modified to obtain the hazard of exiting from the spell. The probability of an investment spike by firm i in the interval (t, t+1], given that it doesn't occur until time t, is:

$$P[t < T_i \leq t+1 | T_i \geq t, x_{it}] = 1 - \exp[-\exp x_i(t)'\beta + \gamma(t))]. \tag{5.4}$$

The log-likelihood function for a sample of *N* individuals can be written as:

$$l(\gamma,\beta) = \sum_{i=1}^{N}\left[\delta_i \log\left[1 - \exp\{-\exp\left[\gamma(k_i) + x_i(k_i)'\beta\right]\} - \sum_{t=1}^{k_{i-1}} \exp\left[\gamma(t) + x_i(t)'\beta\right]\right]\right], \tag{5.5}$$

where δ_i =1 if $T_i \leq C_i$, and 0 otherwise, C_i is a censoring time indicator, and k_i = min(int(T_i), C_i)).

Estimating the log-likelihood function by standard techniques gives the parameter estimates of the covariates (β) and duration dummies (γ). One of the critical assumptions in this formulation is that there is no unobserved heterogeneity. However, ignoring unobserved heterogeneity could lead to an entirely different shape of the hazard due to selection bias (Vauple and Yashin, 1985), and would bias the hazard function downward. Hence, we need to take account of the unobserved heterogeneity effect in our estimation. We assume that the random effect (v_i) is independent of observed covariates and that it enters the hazard function multiplicatively. We further assume that the random effect follows a Gamma distribution with a mean equal to one and a finite variance.[12] The log-likelihood function with the presence of random effect becomes:

$$l(\gamma,\beta,v)=\sum_{i=1}^{N}\log\left\{\begin{array}{l}\left[1+v\sum_{t=0}^{k_{i-1}}\exp\{\gamma(t)+x_i(t)'\beta\}\right]^{-v^{-1}}\\ -\delta_i\left[1+v\sum_{t=0}^{k_i}\exp\{\gamma(t)+x_i(t)'\beta\}\right]^{-v^{-1}}\end{array}\right\}. \tag{5.6}$$

In this empirical section we investigate investment spikes defined as an investment rate of 20 percent or more. This is because small investments that represent routine maintenance and replacement expenditure might not exhibit the timing pattern predicted by the machine replacement model. Although this threshold is arbitrarily set, it is intended to eliminate the routine maintenance and replacement expenditure from the investment analysis.[13] The model is estimated separately for investments on M&E, NMFA, and the aggregated measure TFA – each with and without unobserved heterogeneity.[14] The likelihood ratio test for a null that Gamma variance is equal to zero is readily reported along with the estimation results. A significant result in the LR test implies the existence of unobserved heterogeneity and vice versa.

The primary interest of this analysis is to investigate the shape of the baseline hazard, represented by the coefficients of the duration dummies γ(t). Less negative values are associated with higher hazards. D=0 describes the two spikes that occur in adjacent periods, and D=1 indicates a one year gap between the two spikes. In our estimation we suppress the constant, and are thus able to include the maximum possible duration dummies, 6 periods.[15]

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[12] There are different practices regarding the distribution of the random effect. The non-parametric approach following Heckman and Singer (1984) makes no assumption but approximates the unknown distribution of heterogeneity by a discrete distribution with a finite number of "mass points". The parametric approach on the other hand assumes certain types of distributions such as Gamma, Normal, and Gaussian. Meyer (1990) argues that unlike other distributions, the Gamma distribution is convenient since it gives a closed form expression for the likelihood of avoiding numerical integration.

[13] It is common (among others CHP, 1999; Nilsen and Schiantarlli, 2003) to use a 20 or more percent investment rate as a threshold. These studies have also made a distinction between absolute spike (20 or more percent) and relative spike (when the investment rate exceeds 2.5 times the median investment rate for each firm).

[14] In estimating this discrete time proportional hazard regression model we use *pgmhaz8* in Stata 8.2. This program is developed by Stephen P. Jenkins at the University of Essex. It provides simultaneously both the results with and without unobserved heterogeneity. The built-in model in this program is the Prentice-Gloeckler (1978) model with and without incorporating a gamma mixture distribution.

[15] We have also estimated all models excluding the first duration and including the constant, but we found no qualitative difference particularly on the shape of the hazard.

We have included a number of important variables into the model to control for observed heterogeneity due to shocks and initial conditions. These are profit rate, size, age and industry dummies. Profit rate is defined as the ratio of profit to capital measured by total fixed assets. Size is defined as the number of permanent employees in the firm, and age refers to number of years since the initial establishment. Both size and age are initial values and in logarithm form. We have also included 12 industry dummies.

It is worth noting at this moment that in preparing the data for the hazard estimation, the sample is reduced significantly for the following reasons. First, we use only the first spell, which means that any observation after the second investment spike is discarded. Second, firms without any investment spikes throughout the sample period are also excluded from the data. Third, given that the analysis involves the duration since the last spike firms with an investment spike in the last period are also deleted. As a result, the proportion of firms included in the investment spike estimation is between 42 and 48 percent depending on the type of fixed assets. This means that estimations of the hazard models depend on few firms, which could possibly lead to a loss of efficiency.

Table 4 reports the estimation results of the proportional hazard model with and without unobserved heterogeneity for M&E, NMFA, and TFA separately. For both disaggregated fixed assets (M&E and NMFA), the null hypothesis that the gamma variance is equal to zero is rejected suggesting the importance of unobserved heterogeneity. In the presence of a heterogeneity effect, the magnitude of the coefficients of the duration dummies and the shape of the hazard are found to be entirely different between the models with and without unobserved heterogeneity. Following the model with unobserved heterogeneity, the shape of the investment spike hazard in both types of assets, M&E and NMFA, is monotonically increasing throughout (but only until the fifth period in the latter). This upward sloping hazard of investment spike is consistent with the fixed adjustment costs but not with convex adjustment costs.[16]

Unlike the disaggregated types of fixed assets, we are not able to detect any significant problem of unobserved heterogeneity in the estimation on TFA. The hazard

[16] In a similar specification that allows for unobserved heterogeneity, CHP (1999) found increasing hazard immediately after the initial drop from duration zero to duration one. Nilsen and Schiantarelli (2003) also found a J-shaped hazard for relative spike definition from duration one and onward. Both are considered to be evidence of the importance of fixed adjustment costs.

of investment spike on TFA shows a generally declining trend but not monotonically. This is consistent with convex costs but not with fixed costs. The declining hazard from TFA might be due to the fact that the probability of the second spike increases when aggregating investment expenditures of different types into total fixed assets. This suggests that aggregation of heterogeneous capital might affect the shape of the adjustment cost mainly by smoothing the hazard to imply convex adjustment costs, and also obscures the non-convexity nature of investment pattern. Doms and Dunne (1998) reported in their comparison of plants, firms, and lines of business in US manufacturing, that the higher the level of aggregation, the smoother the capital adjustment.

Table 4 Proportional hazard model results for investment spikes

	Investment spike Non-machinery fixed assets		Investment spike Machinery and equipment		Investment spikes Total fixed assets	
	Unobserved heterogeneity		Unobserved heterogeneity		Unobserved heterogeneity	
Hazard	without	with	without	with	without	with
D0	-2.785***	-3.842***	-2.475***	-3.325**	-2.522***	-2.522***
	(0.485)	(0.938)	(0.464)	(1.631)	(0.432)	(0.434)
D1	-3.235***	-3.565***	-2.886***	-2.054	-3.1212***	-3.121***
	(0.505)	(0.841)	(0.484)	(1.376)	(0.462)	(0.464)
D2	-3.432***	-3.378***	-3.296***	-1.53	-2.941***	-2.941***
	(0.535)	(0.881)	(0.535)	(1.645)	(0.465)	(0.467)
D3	-3.523***	-3.127***	-3.035***	-0.307	-4.003***	-4.003***
	(0.582)	(0.978)	(0.543)	(2.137)	(0.642)	(0.644)
D4	-3.110***	-2.299**	-2.750***	1.259	-2.872***	-2.872***
	(0.609)	(1.139)	(0.586)	(2.966)	(0.558)	(0.559)
D5	-3.596***	-2.452	-2.547***	3.060	-3.302***	-3.302***
	(1.118)	(1.617)	(0.732)	(4.150)	(1.078)	(1.079)
Profit rate	0.0889	0.046	0.011	-4.78E-06	0.113***	0.113***
	(0.063)	(0.056)	(0.058)	(0.132)	(0.046)	(0.046)
Size	0.242***	0.549**	0.430***	1.6125	0.353***	0.353***
	(0.083)	(0.225)	(0.094)	(1.077)	(0.079)	(0.079)
Age	0.044	-0.043	-0.252**	-1.283	-0.098	-0.098
	(0.097)	(0.191)	(0.101)	(0.950)	(0.091)	(0.091)
Tests						
gamma		2.410		6.849		1.28E-06
variance		(1.529)		(5.461)		(0.0008)
gamma var=0						
$\chi^2(01)$		4.29***		6.21***		-4.6e-06
Log-likelihood	-243.94		-237.05	-233.95	-254.42	-254.42
AIC	0.928		0.9878		0.904	
BIC	-2994.90		-2994.07		-3252.96	
# observations	569	569	567	567	607	607
Test1 $\chi^2(5)$	8.01	2.63	7.53	2.74	12.77**	12.77**

Notes: ***, ** and * represent the 1%, 5% and 10% significance levels. Numbers in parentheses are standard errors. We have included 11 industry dummies in the estimation but have not reported them here for brevity. D0, D1 … D5 represent duration. D0 refers to adjacent year. Test1 is LR test for H_0, i.e. all duration dummies are equal each other.

Table 4 also reports test results on the duration coefficients. Given that we do not have a constant in the model, the relevant test for a flat hazard is to find whether the coefficients of the duration dummies are significantly different from each other. The null that all duration coefficients are equal cannot be rejected for M&E and NMFA, while that of the TFA is strongly rejected. This is mainly due to the fact that when controlling the unobserved heterogeneity is important, the standard errors are typically quite large. Recall that we found a large effect of unobserved heterogeneity when we estimated the hazard for the disaggregated capital. Although the hazard of investment spike for M&E and NMFA is increasing, the fact that we can not reject the null that the hazard is flat implies that the evidence in favor of fixed adjustment costs is weaker.

When we look at the effect of other variables, size of a firm affects positively and significantly all types of fixed asset investment spikes. Age is negatively associated with investment in M&E, but is insignificant for investment in NMFA and TFA. The profit rate is positive and significant for TFA, but not for the disaggregated assets.

6. Conclusions

In this paper we examined whether irreversibility and fixed cost of adjustment are important determinants of investment decisions in the Ethiopian manufacturing sector. The descriptive analysis shows that the second-hand market for M&E is almost non-existent, implying that investment is largely irreversible. The percentage of observations with zero investment episodes is very high, ranging from 46 to 60 percent depending on the type of fixed assets. When investment takes place it appears to be lumpy and concentrated in few periods. The inaction is higher and investment lumpier for smaller firms. The large inaction alternating with lumpy investment gives evidence of investment being largely irreversible and of the presence of fixed adjustment costs but not convex adjustment costs. Such an investment pattern is consistent with theories of irreversibility under uncertainty, where firms remain liquid until the marginal return of capital exceeds a certain threshold level.

We applied two econometric methods in identifying the nature of adjustment costs and irreversibility. In the capital imbalance approach we used a non-parametric Nadaraya-Watson kernel smoothing method for investment in two categories of fixed assets, M&E and TFA. For both categories we found a large portion with a flat shape, followed by a positive and non-linearly increasing portion of the adjustment cost curve. The large flat portion represents a longer period of zero investment and suggests that firms do not reduce their capital stock even if the desired capital is much smaller than the actual capital, which is a typical case of irreversibility. The non-linear response of actual investment to capital imbalance is also evidence that firms adjust proportionately more to large deviations of actual from desired capital than to small deviations. Investment is therefore bunched into few periods. This is consistent with irreversibility and fixed adjustment costs.

In the second approach we estimated a proportional hazard model with and without unobserved heterogeneity for a discrete time to test if the probability of investment spikes conditional on the length of the last investment spike exhibits positive duration dependence. In the presence of fixed costs, the productivity gains from an additional investment in the period soon after the first investment are small; thus, the hazard should be upward sloping. In the disaggregated capital, M&E and NMFA, we found an upward sloping hazard consistent with fixed adjustment costs. However, the test for the null that the hazard is flat cannot be rejected, implying that the fixed effect prediction is weaker. For TFA the hazard is declining, which is consistent with convex adjustment costs. The downward hazard in TFA could be due to aggregation of heterogeneous capital. The results from the CHP model however should be taken with some caution, given that the estimation of the hazard model depends on few firms due to our reliance on single spell and that a large proportion of firms do not even see a "beginning" of a spell.

Overall, this study reveals the adverse effect of irreversibility and fixed adjustment costs on the investment decisions of Ethiopian manufacturing firms. A large number of potential investors tend to postpone their investments in an effort to avoid costly mistakes, despite favorable changes in fundamentals. This partly explains the paradox of the low investment but high profit rates documented. Hence, boosting investment requires policy intervention particularly in reducing uncertainty, improving the second-hand market for M&E, and providing better infrastructure since the effects of irreversibility and fixed adjustment costs are more pronounced when there are problems in these areas.

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Data Appendix

Sample selection criterion

The original data consist of 5,182 firm-year observations with 740 firms on average per year. By the very nature of the census, establishments with less than 10 persons engaged are excluded from the data. Since this study involves dynamic analysis we impose a restriction on firms to stay in the data set at least four consecutive years. Due to this restriction 1,832 observations are excluded. We further refined our sample using outlier criteria at which firms with capital stock less than 1000 Ethiopian Birr or firms with negative value added for more than one year are excluded. As a result the final sample contains 478 firms (with 2,845 observations) of which 247 firms are observed the full sample period – seven years.

Capital stock construction

The original data contains capital at beginning of the year, investment, sold assets depreciation, and capital at end of the year. However, due to inconsistency in this construction we take only the beginning year capital stock for the first year where the firm is observed in the data. We subsequently construct the capital stock for each category of fixed assets using the perpetual inventory method.

$$K_{it}^{j} = K_{it-1}^{j}(1-\delta^{j}) + I_{it}^{l} - SK_{it}^{j}$$

In this formula K_{it}^{j} and K_{it-1}^{j} denote capital stock at the beginning and end of the year respectively for each category of fixed assets, δ^{j} is depreciation rate for j type of asset and SK_{it}^{j} denotes asset j sold during the year if any. I_{it}^{j} is deflated investment at year t in asset j. We use depreciation rates of 8% for machinery and equipment, 10% for vehicles and furniture and for fixture, and 5% for buildings.

Definition of variables

Investment (I_{it}) is defined as expenditure minus sales of fixed assets; residential buildings, non-residential buildings, other construction works, machinery and equipment, vehicles and furniture and fixture by firm i at year t. This expenditure is deflated by a GDP deflator (due to absence of separate investment deflator).

The **investment rate** (I_{it}/K_{it}) is calculated by the ratio of the net real investment to the capital stock at the end of the year for the respective category of fixed assets for each firm. When we construct the non-machinery investment rate as a sum of three different categories (non-residential buildings, vehicles, and furniture and fixture) we add the deflated investment and constructed capital stock to take the ratio of these sums. The total fixed assets investment rate is also constructed from all categories by the same method.

The **profit** is found by subtracting total wages and salaries paid (for permanent and temporary workers) plus cost of employee benefits from value added at factor cost, and the **profit rate** is defined as a ratio of this profit to total fixed asset capital stock.

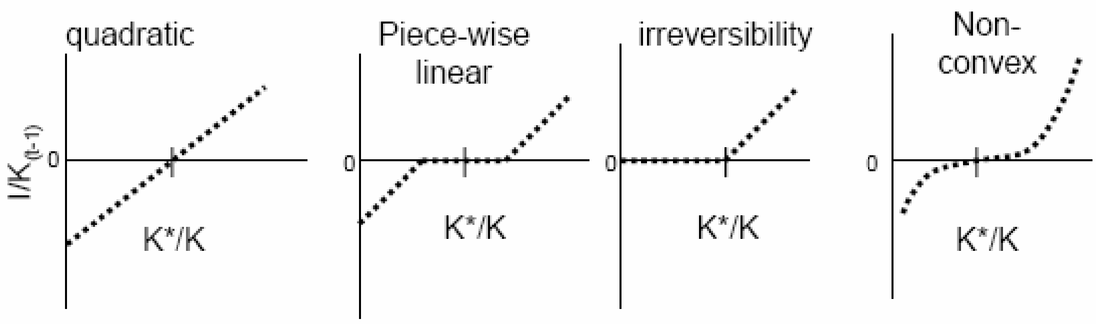
Age of a firm is found by subtracting the startup year from current year plus one.

Table A1 International comparison of investment and profit rates

Country	percentage of observations with: zero investment	percentage of observations with: I/K>=20%	$I/K_{(t-1)}$ mean	$I/K_{(t-1)}$ median	profit rate mean	profit rate Median	percentage of observations sold: M&E	percentage of observations sold: M&E>=10% of capital
Belgium			0.125		0.239			
France			0.11		0.222			
Germany			0.122		0.218			
UK			0.117		0.198			
USA	8.1	18	0.122					
Norway	21	12						
Spain	18	24.7						
Cameroon	71		0.122	0	1.556	0.36		
Ghana	68		0.133	0.004	3.696	0.707		
Kenya	58		0.119	0	1.956	0.32		
Zimbabwe	34		0.134	0.033	0.918	0.422		
Zambia	69							
5 African countries Average	58		0.128	0.005	1.98	0.403	0.14	0.01
Ethiopia	59.7	13	0.15	0	2.19	0.48	0.06	0.01

Notes: the source for the first four European countries is Bond, Elston, Mairesse, and Mulkay (1997), for Norway Nilsen and Schiantarelli (2003), for Spain Rocio Sanchez-Mangas (2002), for USA Cooper and Haltiwagner (2000), and for the five African countries Bigsten et. al (2005), whereas the mean investment rate and profit rate for four African countries are found in Bigsten et. al (1999b).

Figure A2 Implied shape of various adjustment costs



Where $I/K_{(t-1)}$ actual investment and K^*/K equals mandated investment
Adopted from Golsbee and Gross (1997)