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The Effect of Credit on Growth and Convergence of Firms in Kenyan Manufacturing

Janvier D. Nkurunziza[†]
United Nations Economic Commission for Africa
P. O. Box 3005 Addis Ababa, Ethiopia
Telephone: 251-1-443-614
Email: Jnkurunziza@uneca.org

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Abstract:

Although some recent studies have analysed issues relating to credit in African manufacturing, they have not directly tested for the effect of credit on firm growth. The use of bank credit can affect firm growth in two opposite ways. The effect may be positive if credit allows a firm to address its liquidity constraint and increase profitability. However, if macroeconomic shocks such as increases in interest rates make firm debts unsustainable as experienced in Kenya in the 1990s, indebted firms may shrink or even collapse. Hence, empirical testing is necessary to determine which effect dominates in a specific case. Using microeconomic data on the Kenyan manufacturing sector, the study finds that conditional on survival, the firms that use credit grow faster than those not using it. This result is robust to alternative estimation procedures, controlling for both endogeneity of the credit variable and selection bias. Convergence in firm size is significant in all the models except the GMM estimation that controls for several forms of endogeneity. The significance of convergence contradicts Gibrat's law of proportionate effects while supporting Jovanovic's learning hypothesis.

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1. Introduction

The use of bank credit can affect firm growth in two opposite ways. The effect may be positive if credit allows a firm to address its liquidity constraint, increasing profitability and firm expansion. However, similar to other African economies struggling to cope with macroeconomic instability resulting from the introduction of liberalisation measures in the late 1980s and early 1990s, Kenya experienced strong macroeconomic shocks in the 1990s. For instance, interest rates doubled while the Kenyan shilling was repetitively devalued in the first half of the 1990s. These conditions may have forced indebted firms to shrink or even collapse. Hence, only empirical testing may show specifically how the use of credit affected the growth of Kenyan firms.

This paper is an empirical study of the effect of initial size and access to credit on Kenyan firms' rates of growth. Notwithstanding the limits imposed by available data, the paper shows that the use of credit increases surviving firms' growth, lending support to firm managers' claim that access to credit is one of the main problems they face. This finding is robust to several estimation methods, namely OLS, nonlinear least squares (NLS), instrumental variable (IV), fixed effects (FE), GMM, and Heckman's selection model. Furthermore, the paper finds evidence that small firms have higher rates of growth (or lower rates of decline) than large ones supporting the convergence hypothesis but contradicting Gibrat's law of proportionate effect.

The work in this paper is akin to the studies of the Industrial Surveys in Africa (ISA) Group whose research on African manufacturing over the last decade is a landmark. Among the aspects of African manufacturing covered by the members of the Group, collectively and individually, are the following: investment [Bigsten*, et al.* (1999b); Soderbom and Teal (2000)], inventory holding as a risk coping mechanism [Fafchamps*, et al.* (2000)], firm survival [Harding*, et al.* (2004)], firm growth and productivity [Teal

(1999)], returns to human and physical capital [Bigsten Arne*, et al.* (2000)], contract enforcement [Bigsten A.*, et al.* (2000); Fafchamps (1996)], exports of manufactured products [Bigsten*, et al.* (1999a)], credit constraints [Bigsten*, et al.* (2003); Fafchamps*, et al.* (1994); Fafchamps (2000); Fafchamps*, et al.* (1994); Fafchamps*, et al.* (1995)], and trade credit [Fafchamps (1997)].

We devote special attention to the potential problem of endogeneity between access to credit and firm growth. In the first part, an instrumental variable approach using information on firm start-up is pursued to account for endogeneity. In the second part of the analysis, data covering the period 1992-1994 is used to estimate fixed effects and GMM models to account for potential endogeneity due to unobserved heterogeneity. Given that only surviving firms can grow, we test for the significance of the selection bias and its impact on the effect of the credit variable.

The main contribution of the paper is to show the effect of credit use on a firm's rate of growth amidst macroeconomic instability. Although some of the studies cited above have dealt with the issue of credit in African manufacturing, they have not directly tested for the role of credit on firm growth. Moreover, many studies analysing firm growth have estimated OLS models [see for instance Evans (1987a), Evans (1987b)] which do not account for endogeneity and selection bias in a systematic way. These studies produce misleading results as Teal (1999) has shown. When he estimates a simple OLS model, he finds evidence of convergence. However, accounting for endogeneity makes convergence insignificant.

The analysis uses two sample periods. The first period is from firm creation to the first time a firm was sampled, namely the years 1992 and 1999.[1] The second period is a panel of three-year data points covering the years from 1992 to 1994. The main difference between these two periods is shown in the average growth rates. Before 1992,

[1] The question on the size of a firm at start-up was only asked in 1992 and 1999.

firms were growing at a yearly average rate of 7 percent. However, firms that entered the sample in 1999 post a negative rate of -1 percent and the average growth rate of firms observed over the period from 1992 to 1994 is about -2 percent. The difference in growth rates is probably due to the crisis that hit the Kenyan economy in the 1990s.

The paper proceeds as follows. In Section 2, we discuss the literature on the determinants of firm growth, focusing on the role of credit and convergence. Section 3 derives the empirical equation of growth which we estimate by NLS, OLS and IV using data on firm start-up. Section 4 re-estimates the growth model by fixed effects and GMM techniques to address different aspects of the potential problem of endogeneity. The data used is a panel covering the period from 1992 to 1994. Section 5 estimates a Heckman Full Information Maximum Likelihood (FIML) model to correct for a potential self-selection bias. Section 6 concludes and proposes some issues for further research.

2. Literature on Credit and Firm Growth

This section discusses the literature on the effect of credit on firm growth followed by a brief overview of the different theories of firm growth, their contradictions and implications for firm growth in Kenyan manufacturing.

2.1. How Does the Use of Credit Affect Firm Growth?

The use of bank credit can affect firm growth in two opposite ways. The effect may be positive if credit allows a firm to address its liquidity constraint, becoming more profitable and leading to firm expansion. However, in economies with macroeconomic instability, the increase in interest rates increases the stock of debt, which may destabilise firms and eventually force them to shrink or even collapse.

Macroeconomic growth regressions show some evidence of the importance of financial factors in the process of economic growth [see Easterly and Levine (1997), King and Levine (1993)]. At the microeconomic level, there is a widely held view that slow growth of firms in Africa is the result of a lack of access to financial resources [see Levy (1993); McCormick*, et al.* (1997); Biggs and Srivastava (1996)]. Moreover, the neoclassical literature analyses the effect of financial market imperfections on investment [see Fazzari*, et al.* (1988); Hubbard (1998); Hubbard*, et al.* (1995); Ndikumana (1999)], which may provide the link between access to credit and firm growth. As firms are credit rationed [Jaffee and Russell (1976); Stiglitz and Weiss (1981); Bigsten*, et al.* (2003)], they may be forced to curtail investments.

Credit is less of a constraint in developed countries than in Africa. Audretsch and Mahmood (1995: 12) report on the results of a survey showing that in the U.S. "only 12 percent of managers and owners of companies with 6 to 500 employees considered 'difficulty in obtaining' financing to be the 'most serious problem' for their company". In contrast, most firm managers in Africa complain that credit is the most serious impediment to their activities. Two reasons explaining this difference may be the diversified financial markets in developed economies and the fact that developed economies rarely experience credit and other economic shocks of the magnitude seen in developing economies.[2]

In developing economies, credit is often regarded not as a business deal but rather as a favour. Before the liberalisation of the financial sector in Tanzania in the early 1990s, even after fulfilling all the pre-conditions attached to lending,[3] securing a loan still required side payments from applicants and the processing of loan applications took six months on average [Levy (1993)]. In this context, firms prefer retained profits as the

[2]The problem of funding seems to be shared by firms in transition economies of Eastern Europe [see for example, Brown*, et al.* (2003)].

[3] Feasibility studies were only a part of the requirements, even for overdraft credit.

most reliable source of investment finance in Africa. In this light, the study by Bigsten*, et al.* (1999b) has found that investment in African manufacturing is positively related to profit levels although estimated elasticities of investment to profit are relatively small.

The relationship between credit and growth may be through channels other than investment. For example, access to external resources allows flexibility in resource allocation [see Fafchamps (1997)]. In periods of crisis when customers are unable to pay on time as is often the case in many African economies [Fafchamps (1996); Bigsten*, et al.* (2000)] bank loans limit the impact on firm activity of the drop in firms' cash flow, allowing them to function normally.

Moreover, firms with access to funding are able to "build up inventories to avoid stocking out when faced with demand shocks or late input delivery" [Fafchamps*, et al.* (2000: 861)]. Hence, about two-thirds of firms in Kenya say that without credit facilities, they would respond to a liquidity problem by cutting down production and limiting their size [Fafchamps*, et al.* (1994)]. As a result, firms with limited internal reserves may be forced to close down or postpone strategic investments if they do not have access to bank funding. Firms without access to bank funding, especially overdrafts, are also vulnerable to external shocks.

In this light, with financial market imperfections, asymmetric information and agency costs affecting more adversely small borrowers in Africa's credit markets [Azam*, et al.* (2001); Bigsten*, et al.* (2003); Fafchamps (2000); Fafchamps (1997); Raturi and Swamy (1999); Atieno (1998); Aryeetey*, et al.* (1997)] small firms may never be able to borrow from the formal market in order to invest and grow. This suggests that the differences in firm growth may be explained by start-up conditions. High-budget firms or those able to borrow are able to start with an efficient size that allows them to grow faster [Shorrocks (1988); Mengistae (1998)]. Geroski (1995) found that firms creating new plants in the USA establish units that are larger than the average incumbent. These plants grow to a size 2.5 times larger that that of the average incumbent over a period of ten years. There may be, therefore, a direct relationship between access to finance, start-up size and firm growth.

2.2. Initial Size and Theories of Firm Growth

Firm size is important in developing economies. For instance, many believe that micro and small firms in those economies are the most vibrant businesses in terms of job creation and income generation [Reineccke (2002); Mead and Liedholm (1998); McPherson (1996); Mead (1994)].[4] On the other hand, large size is important in African manufacturing because they may realise scale economies. Moreover, large firms have more capacity to lobby government officials for favours ranging from tax exemptions to the awarding of contracts [Gauthier and Gersovitz (1997); Mead and Liedholm (1998)].

How does initial size relate to firm growth? One of the oldest propositions regarding the relationship between firm size and the rate of growth is due to Gibrat (1931). In his celebrated 'Law of Proportionate Effect (LPE)', he postulates that firms' rates of growth are independent of their initial sizes. As Mansfield (1962: 1031) puts it, Gibrat Law implies that "the probability of a given proportionate change in size during a specified period is the same for all firms in a given industry, regardless of their size at the beginning of the period".

This proposition is disputed by Bain (1956) who argues that there is a Minimum Efficient Scale (MES) which is achieved when a firm attains a size corresponding with the minimum long run average cost. Firms with sizes smaller than the MES enjoy economies of scale until they reach the MES but all firms beyond the MES are characterised by constant returns to scale. Hence, firms below the MES experience

[4] This view is based on contested results of studies carried out in the 1970s and the 1980s by, among others, Birch (1987); and Brown*, et al.* (1990).

slower growth, on average, relative to those with the optimal size, contradicting Gibrat's law.

The third theoretical strand is associated with Lucas (1978) and Jovanovic (1982). Lucas' thesis is that the equilibrium size distribution of firms depends on the distribution of managerial capabilities within a population. According to this argument, any firm size may be optimal given its manager's ability. Building on Lucas' theory, Jovanovic (1982) proposes a 'learning model' in which firms learn about their efficiency levels once they are established; managers 'guess' their firms' efficiency from a distribution of efficiency rates. As managers learn from their past guesses they update their information base and formulate better guesses in the future.

This process narrows the variance between the guessed and the actual levels of efficiency as firms grow older. According to Jovanovic (1982: 656) "younger firms have more variability in their growth rates. They will also grow faster than the older firms" as the productivity parameter of mature firms converges to a constant. Jovanovic's model, therefore, predicts a negative relationship between age and firm growth.

The problem with Jovanovic (1982) model is that it is static as it keeps the efficiency parameter fixed. Pakes and Ericson (1987) extend the model by invoking human capital formation as a way of altering the efficiency parameter. Their model assumes that managers possessing the largest stock of human capital are better placed to make the best guesses, implying that they are capable to run their firms more efficiently. As a result, firms with high human capital register higher rates of growth relative to those with low human capital.

Directly or indirectly, the theories of firm growth assume growth to be every firm manager's objective. However, there may be cases where firms have a different objective. The first case is when economic conditions are so hard that firms fight for survival rather than growth. Secondly, as Lucas (1978) theory shows, some small firms may be at their equilibrium sizes, choosing to remain small if they realise returns to their entrepreneurial ability [Asea (1996)]. Thirdly, firms may not need to grow if they occupy strategic niches that are better served by small size [Agarwal and Audretsch (1999)]. There may be also firms that choose to grow horizontally [Bigsten (2002)], especially in the informal sector.

Moreover, firm growth entails a transformation that has advantages but also disadvantages. Growing from a small informal firm to a large business has the advantage of formal institutional recognition and the benefits accompanying it. They include more prestige and more ability to raise external resources. However, this form of growth has also participation costs such as higher taxation and more social responsibilities for the firm owner [see Levenson and Maloney (1998)]. If the benefits of growth are outweighed by the costs, a firm may rationally choose not to grow. Nonetheless, our assumption in this paper is that growth is the objective of most firms.

2.3. Using Insights from the Growth Model to Analyse Firm Convergence

We empirically analyse firm growth and convergence using insights from the Solow growth model used in empirical macroeconomic studies. One key assumption underlying the Solow model of economic growth is that individuals save a fixed share of their income. These savings are invested to accumulate capital which in turn is rented out to firms for use in productive activities. Whether capital and output grow depends on their position relative to the steady state. Below the steady state, individuals have an incentive to invest and accumulate more capital. Beyond the steady state, the capital stock is reduced until it reaches the steady state level [see Jones (2002)].

In this regard, economies with the same level of technology, same investment rates and same population growth share the same steady state. Among these economies, those with the lowest levels of capital grow faster towards the steady state. This description corresponds to what is termed ***absolute*** convergence hypothesis. It states that on average, among countries with the same steady state, poor countries should grow faster than richer ones.[5] Barro (1991) calls the process $\beta - convergence$. However, in reality, countries may have different steady states. In this case, $\beta - convergence$ becomes ***conditional*** as it measures the effect of initial income level on the rate of growth, controlling for the determinants of the steady state.

A third concept, $\sigma - convergence$, relates to the tendency of the dispersion in income measured, for instance, by standard deviation, to decline over time. Barro and Sala-i-Martin (1990) show that over time, the variance in the size distribution falls (or rises) if the initial variance in the size distribution is greater than (or less than) the steady state variance. In other words, $\beta - convergence$ is necessary but not sufficient for $\sigma - convergence$ [Barro and Sala-i-Martin (1990: 13)].

Using a methodology developed for macroeconomic analysis to analyse a microeconomic question does not pose a fundamental problem, as long as the methodological analogy is appropriate. After all, the methodology championed by Quah (1993b) and Quah (1993a) to analyse differences in economic growth across countries was initially designed to study the patterns of income distribution and earnings mobility in the microeconomic literature.

Therefore, the model of individual accumulation underlying growth is not fundamentally different from the pattern of firm evolution. Many firms start small, save, invest and grow, the same way an economy does. Also, firms may have a steady state size beyond which additional growth is not beneficial. As in the growth literature, it is reasonable to assume that small firms below the steady state size display higher growth

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[5] The convergence hypothesis in Macroeconomic analysis has been attributed to the work of Solow (1956). However, Mankiw, *et al.* (1992) note that "the Solow model does not predict convergence… [It] predicts convergence only after controlling for the determinants of the steady state, a phenomenon that might be called 'conditional convergence'". Quah (1993a) argues that neither absolute nor conditional convergence defined as above measure the growth of small firms relative to large ones.

rates than firms close to the steady state. This catch-up process is similar to the concept of convergence discussed above. Hence, firm convergence implies that the relationship between start-up or any past size and the growth rate is negative. This paper uses the concept of conditional $\beta - convergence$. It is clear that the convergence hypothesis violates Gibrat's law but is in agreement with Jovanovic's interpretation.

Empirically, it is usually found that Gibrat's law holds only for firms larger than a certain size [Bain (1956); Evans (1987a); Hall (1987); Mansfield (1995); Simon and Bonini (1958)]. Recent empirical studies of Africa's manufacturing have found some evidence of convergence. Examples include Ethiopia [Mengistae (1998)] and Burundi [Sleuwaegen and Goedhuys (1998)]. A similar relationship has also been found to hold in studies of small firms in Botswana, Kenya, Malawi, Swaziland and Zimbabwe [see Mead and Liedholm (1998)]. This latter study found a positive relationship between initial size and growth in the Dominican Republic. In Ghana, Teal (1999) found that once endogeneity is controlled for, there is no evidence of convergence.

2.4. Other Factors Affecting Firm Growth

In addition to size, age and credit, another factor that may explain the differences in firm growth in Kenya is the ethnic background of the owner. The importance of this variable for firm performance in Africa has been highlighted by a number of authors including Collier and Gunning (1999); Fafchamps (1997); Fafchamps (2000); Fisman (2003); Fisman (1999); and Raturi and Swamy (1999). The growth of firms owned by Kenyans of African origin is expected to be slower than firms owned by Kenyans of Indian origin. The reason is that country's manufacturing sector has been dominated by Kenyans of

Indian origin for a long time.[6] The sector of activity and the location of a firm may also be important determinants of its rate of growth.

3. Estimating a Convergence Equation Using Start-up Data

The first sub-section derives the empirical convergence equation. The second sub-section presents the empirical data and the third subsection discusses estimation issues and empirical results.

3.1. Deriving a Convergence Equation

Empirical testing of the theories of firm growth discussed in the previous section is performed on the basis of a convergence equation.

3.1.1. The Basic Growth Equation

What is the theoretical basis for growth regressions? This question is rarely asked when empirical models of growth are estimated. Almost every author derives a growth equation from a Solow model by log-linearising around the steady state. This approach has critics.[7]

Elbers and Gunning (2001) argue that growth regressions have no sound theoretical basis for three reasons. First there is no economic behaviour in the Solow model because 'capital accumulation has no choice-theoretic basis.' Secondly, the model is deterministic as it does not incorporate uncertainty. To address these two issues, the authors suggest the use of models belonging to the class of the stochastic Ramsey framework. The third criticism is about log-linearising around the steady state.

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[6] To understand the process leading to this situation, see Phillips, *et al.* (2000); Bigsten (2002); and Delf (1963).

[7] This critique is different from that levelled by Danny Quah.

Elbers and Gunning find that there is only one log-linear model in the class of stochastic Ramsey models that generates a canonical growth equation. However, they caution that the model is implausible for two reasons: capital depreciates fully within one period and changes in risk have no impact on investment. Given these shortcomings, the authors propose that the log-linear growth specification should be abandoned.

These criticisms of growth regressions are founded and we address them as follows. Firstly, as we do not assume a constant savings rate, the first criticism regarding capital accumulation does not affect our analysis. Secondly, we agree that the growth models in this paper do not capture uncertainty. This issue is addressed in a different paper on firm mobility where firm growth and exit are modelled in a unified framework [see Nkurunziza (2004)]. Exits reflect the extent to which shocks, particularly the shock to interest rates and other macroeconomic variables, affected firm survival in the 1990s. The last criticism regarding log-linearising around the steady state is also addressed in the same paper where we analyse growth by modelling the distribution of firm size rather than log-linear models.

We derive a basic convergence equation where a firm with a start-up size $\ln(S_0)$ reaches its steady state size $\ln(S^*)$ when $d\ln(S_t)/dt = 0$. The transitional dynamics to steady state is assumed to be approximated by the following differential equation:

$$\frac{d\ln(S_{it})}{dt} = \beta\left[\ln(S^*) - \ln(S_{it})\right] \tag{1}$$

where subscripts i,t refer to firm and time period, respectively, with $i = 1,2,...N$ and $t = 1,2,...T$. Hence, $\ln(S_{it})$ is firm i^{th} size at time t and $\ln(S^*)$ is the steady state size determined by a vector of variables x_i.[8] β is the rate of convergence towards the steady state. Hence the bracketed term at the right hand side of equation (1) is the 'distance'

[8] In Barro and Sala-i-Martin (1992), x is the rate of exogenous labour-augmenting technological progress.

between current and steady state size. The relation $\ln(S^*) = \ln(S_{it})$ may not be observed either because firm i is not in steady state at time t or because the firm has its own long run equilibrium size that differs from $\ln(S^*)$. Equation (1) may be rewritten as a non-homogeneous first-order differential equation that is mathematically manipulated to yield an estimable growth equation:

$$\frac{d\ln(S_{it})}{dt} + \beta\ln(S_{it}) = \beta\ln(S^*) \tag{2}$$

Solving equation (2) for $\ln(S_{it})$ using the complementary function $Ae^{-\beta t_i}$ and the particular integral $\ln(S^*)$ (assuming $\left[\left(d\ln(S_{it})/dt\right) = 0\right]$ following convention):[9]

$$\ln(S_{it}) = e^{-\beta t_i}\ln(S_{i0}) + \left(1 - e^{-\beta t_i}\right)\ln(S^*) \tag{3}$$

In order to derive an estimable firm growth model from equation (3), we subtract $\ln(S_{i0})$ from both sides, divide through by t_i and add a stochastic error term u_i:

$$\frac{\left[\ln(S_{it}) - \ln(S_{i0})\right]}{t_i} = \frac{-\left(1 - e^{-\beta t_i}\right)}{t_i}\left[\ln(S_{i0})\right] + \frac{\left(1 - e^{-\beta t_i}\right)}{t_i}\left[\ln(S^*)\right] + u_i \tag{4}$$

Note that the coefficient of $\ln(S_{i0})$ varies with t_i, the time elapsed since firm creation. Hence, estimating equation (4) requires nonlinear least squares. The left-hand side of equation (4) is i^{th} firm average annual rate of growth. The transformation from equation (3) to equation (4) is necessary if t_i varies across firms. This problem does not arise in macroeconomic growth regressions since countries are observed either using the same time interval in panel data or using the same period of observation for all countries.

To test for the theories of firm growth discussed above, we are first interested in determining the size and sign of the coefficient on initial size given as:

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9 See Chiang (1984), chapter 14, for a simple treatment of first-order differential equations.

$$\lambda_i = -\frac{\left(1 - e^{-\beta t_i}\right)}{t_i} \tag{5}$$

For given values of age, the convergence parameter β can be recovered from equation (5) when λ is estimated instead of β. It is also relevant to note that $\frac{\partial \lambda}{\partial \beta} > 0$ so qualitatively, a high $\lambda - coefficient$ implies a high convergence rate. Convergence à la Barro is established when β is significant.

3.1.2. Variables Used to Estimate the Empirical Equation

What are the variables used to empirically test the theories of firm growth and what are their predicted signs? As discussed above, initial size should not be significant according to Gibrat's law. According to the MES principle, size is positively correlated with growth at least up to the MES. However, Jovanovic (1982) proposes an opposite prediction. He explains that young firms are usually small and that surviving firms increase their size as they become more experienced. This process predicts a negative relationship between firm size and growth.

Regarding the variables that capture the steady state, we use age, credit use and ethnicity of the firm owner. Age is used to proxy for a firms' learning process and its movement to steady state. Equation (4) shows that the variable age is integrated in the computation of the convergence coefficient through t_i. Therefore, age is in the vector of variables explaining steady state only in cases where the period of observation is the same across firms.

Introducing credit in the growth equation changes the transitional dynamics. In an economy with a perfect capital market, steady state size may be achieved instantaneously through borrowing. In this case, there are no transitional dynamics of interest [see King and Rebelo (1993)]. In theory, a firm with unrestricted access to credit would start with a size exactly equal to the steady state size. However, in reality, this may not be the case for two reasons.

Firstly, in light of Jovanovic (1982) models, firms at start-up may not know their steady state size. Secondly, start-ups in African economies cannot be assumed to be credit unconstrained. Evidence in RPED data shows that 80 percent of start-ups use personal savings to fund their capital and Bigsten, *et al.* (2003) establish that firms in Africa are credit constrained. Therefore, the hypothesis that a firm in Africa uses credit at start-up to reach its steady state in one period is not tenable. Credit is expected to have a positive and significant relationship with firm growth. With respect to ethnicity of the owner, firms owned by Kenyans of African origin are expected to grow less than firms owned by Kenyans of Indian origin.

3.2. Descriptive Statistics and Construction of the Variables

The data is divided into two samples. The first sample uses start-up information for 224 firms surveyed in 1992. The second is made up of about 70 firms that were surveyed for the first time in 1999 and provided information on their start-up conditions. The models compare results on the full sample and on the two sub-samples separately. A pooling test rejects the null, suggesting that the new firms entering the sample in 1999 were not drawn from the same distribution as those from 1992. Therefore, although we show the results of the pooled sample, we base our discussion on the sub-samples.

Table 1: Descriptive Statistics for the Models Using Start-Up Variables

	Full Sample			1992			1999		
Variables	Mean	S. D.	Obs.	Mean	S. D.	Obs.	Mean	S. D.	Obs.
Growth Rate	0.05	0.23	278	0.07	0.19	208	-0.01	0.30	70
Ln current Size	2.82	1.75	352	2.85	1.82	224	2.75	1.63	70
Ln start-up Size	2.09	1.40	278	2.04	1.41	208	2.22	1.38	70
Age	16.46	13.40	350	17.32	13.67	224	14.47	11.55	70
Ln age	2.40	1.03	350	2.48	0.98	224	2.24	1.08	70
Square ln age	6.80	4.30	350	7.12	4.23	224	6.15	4.20	70
Ln (age*size)	5.39	4.53	278	5.39	4.53	208	5.37	4.54	70
How Long C/A	16.80	12.59	265	15.85	12.24	183	17.31	11.96	45
Loan at start-up	0.19	0.39	352	0.24	0.43	224	0.07	0.26	70
Kenyan African	0.42	0.49	352	0.41	0.49	224	0.47	0.50	70
Kenyan Indian	0.44	0.50	352	0.46	0.50	224	0.40	0.49	70
Other Ethnicity	0.14	0.34	352	0.13	0.34	224	0.13	0.34	70

The size variable used is the log of a firm's number of full time workers. The choice of this variable is standard practice in the literature on developing economies. The variable is relatively easy to count and it does not need to be deflated unlike alternative measures. For instance, sales, production and profitability are thought to be more prone to large measurement errors (and need to be deflated) than the 'number of workers' variable.

Some studies have found an association between the change in the number of workers and other measures of firm activity. Mead and Liedholm (1998) report findings of studies that have found that in Kenya and in the Dominican Republic, the growth in real sales is twice that in the number of workers. They conclude that the use of the number of workers variable may be considered as a conservative, lower-bound estimate of net firm expansion.

Growth rate, size, age and how long has a firm had a current account are continuous variables. All the other variables are binary. The credit variable takes value 1 if a firm used a bank loan to finance part of or all its start-up capital and zero otherwise. The ethnicity dummies capture the ethnic background of the owner. We distinguish between Kenyans of African origin, those from Asian descent (we call them Kenyans of Indian origin as Kenyans of Asian descent originated principally from India) and Others. This latter group is made up of non-Kenyans, Kenyans of Middle Eastern origin and a few observations we could not place in either of the first two groups.

The variable whether a firm used credit at start-up measures more directly the impact of access to bank credit on growth. It may be argued that the amount of credit used is a better measure of a firm's involvement with the banking sector. There are different reasons why we do not use this measure. First, we are not primarily interested in the impact of the amount of credit on firm growth. The question of direct interest to our analysis is whether or not a firm has had access to bank loans not how much it secured. If a firm secures access to bank finance, it breaks an important entry barrier into the credit market. Once in the market, reputation makes it relatively easy to negotiate the amount of the loan as studies on informal credit have shown [see, for instance, McMillan and Woodruff (1999b)].

The second reason for not using the amount of credit is that the variable is plagued with measurement errors. It is no secret that firms manipulate their balance sheets to evade taxation and the amount of outstanding credit is one of the variables they manipulate. Thirdly, in the period 1992-1994, many firms did not respond to this question so there are relatively few observations. When we use the variable (lagged), only 30 percent of the sample remains (from about 315 to about 90 observations) raising the fear of a severe selection bias.

3.3. Estimation Issues and Empirical Results of Models Using Start-up Variables

The use of the data raises a number of econometric issues. These are nonlinearity, endogeneity and self-selection. We discuss first the issue of nonlinearity which is relevant only for analyses using start-up variables. Secondly, we analyse the problem of simultaneity and heterogeneity.[10]

3.3.1. Nonlinearity

Estimating the model in equation (4) by OLS may produce biased parameters as it is clearly nonlinear in parameters. As time (or firm age) goes to infinity, λ goes to zero; implying that the influence of initial size on a firm's rate of growth is stronger the younger the firm. Therefore, β and λ must be estimated using nonlinear least squares (NLS) method [see Wooldridge (2002)]. The extent to which the NLS results differ from OLS qualitatively and quantitatively is shown by comparing estimates from the two procedures.[11]

To account for the nonlinearity in the relationship between firm growth and its explanatory variables in OLS models, we will estimate a growth model with squared log of age.

3.3.2. Endogeneity Due to Simultaneity and Heterogeneity

Reverse causation between access to credit and firm growth is a potential source of endogeneity. It is plausible that the firms using credit are the ones that grow, suggesting causality from growth to credit use. Hence, estimating equation (4) by OLS produces biased results. To address the problem, we estimate current growth on start-up credit use.[12] Using start-up credit could still be correlated with firm specific factors that

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[10] Analysis covering the period 1992-1994 addresses the potential problem of endogeneity by using panel data techniques. The same data is used to address the problem of self-selection.

[11] This problem concerns only the models using start-up information. In the period post-1992, all firms are observed over the same period even when they have different ages. Hence OLS models can be estimated, but such estimation raises other issues that we discuss below.

[12] However, even if credit is pre-determined, it could be argued that credit use was based on expected growth, a problem we address in the next section with panel data models.

simultaneously determine credit use and growth. Firms that used start-up credit were probably particular, and the factors that allowed them use credit may be the same explaining their growth. To eliminate this source of bias, we instrument credit drawing on firm and owners' characteristics that are correlated with credit but not with growth.

Table 2: NLS and OLS Models from Start-up to 1992 and 1999
Dependent variable is annual growth rate in firm size

	Nonlinear Estimation			OLS Estimation		
	Full	1992	1999	Full	1992	1999
Bank loan at start-up	2.02***	2.03***	-0.24	0.06***	0.06***	-0.10
	[0.55]	[0.75]	[0.60]	[0.02]	[0.02]	[0.06]
	(0.12)	(0.12)	(-0.02)			
$\beta - Parameter$	0.31***	0.06***	0.64***	0.20	0.07	…
	[0.09]	[0.02]	[0.11]			
Ln(start-up size)	-0.06	-0.04	-0.07	-0.06***	-0.04***	-0.10***
	(average)	(average)	(average)	[0.02]	[0.01]	[0.02]
Ln(age)				0.13	-0.05	0.48***
				[0.10]	[0.10	[0.15]
Ln(age) squared				-0.03*	0.0003	-0.10***
				[0.02]	[0.02]	[0.03]
Kenyan of Africa origin	-0.73***	-0.87	-0.34	-0.13***	-0.12***	-0.15**
	[0.30]	[0.65]	[0.35]	[0.03]	[0.03]	[0.07]
Other ethnicity	0.38	-0.58	1.07***	-0.02	-0.11	0.05
	[0.65]	[1.93]	[0.43]	[0.05]	[0.09]	[0.05]
Textiles sector	1.44***	1.02	1.12***	0.02	-0.02	0.06
	[0.39]	[0.76]	[0.37]	[0.04]	[0.03]	[0.08]
Food sector	1.42***	0.31	2.41***	0.03	-0.04	0.17
	[0.37]	[0.96]	[0.34]	[0.04]	[0.03]	[0.11]
Metal Sector	1.79***	2.04**	1.40***	0.07*	0.03	0.12
	[0.44]	[1.00]	[0.40]	[0.04]	[0.04]	[0.09]
Constant	0.12***	0.11***	0.14***	0.10	0.33***	-0.26
	[0.02]	[0.02]	[0.02]	[0.13]	[0.12]	[0.19]
R-squared	0.22	0.09	0.70	0.15	0.15	0.48
Adjusted R-squared	0.20	0.06	0.66	0.12	0.11	0.40
Log Likelihood	53.33	58.50	26.92	39.95	65.39	7.63
Number of observations	278	208	70	278	208	70

Numbers in brackets are White (1980) heteroskedasticity-consistent standard errors. Numbers in parentheses on the credit variables are adjusted from NLS estimates for comparison with OLS parameters. Three, two and one star, correspond to 1 percent, 5 and 10 percent significance level, respectively. The reference groups are Kenyans of Indian origin for ethnicity and wood for sector of activity. Coefficients on the log of start-up size in the NLS models are averages.

Equation (4) is estimated nonlinearly in the first three columns. The $\beta - Parameter$ is directly estimated in the NLS model but the corresponding values for OLS are implied on the basis of equation (5).[13] The coefficients on start-up size in the NLS model are derived using the same approach. It is noteworthy that implied NLS coefficients of the start-up variable are equal or close to OLS coefficients, implying that the two models predict the same effect of initial size on firm growth. The implied convergence rates from the two models are also very close.

NLS coefficients must be adjusted before they can be compared with OLS parameters. The reason is that NLS coefficients are function of age. NLS estimation procedure computes $\widehat{\gamma}_{NLS} = \widehat{\delta} * \lambda_i$ where $\widehat{\delta}$ is the coefficient reported in Table 2, and λ_i is the variable given in equation (5). Since λ_i varies according to the age of a firm, it is possible to compute an 'average' NLS coefficient $\overline{\gamma}_{NLS} = \widehat{\delta} * \overline{\lambda}$ using average age. Applying this procedure, the coefficients on the credit variable are shown in Table 2 in parentheses below the standard errors.

A quick inspection of NLS and OLS shows that both models capture the significance of the two variables of interest, namely credit use and start-up size. The following discussion is based on NLS results.

Credit and Growth: The use of the variable credit access at start-up is an attempt to address the problem of endogeneity due to reverse causation. Access to bank credit appears to have a positive effect on firm growth in 1992 but not in 1999. The positive sign and significance of the coefficient in 1992 suggest that firms that use credit record higher growth rates than those without access to credit. The size of the coefficient is 0.12

[13] The implied $\beta - Parameter$ for 1999 could not be calculated as it required the computation of the log of a negative value.

in 1992 (and 0.06 for OLS), implying a substantial effect of credit on growth. As expected, in the 1990s, the coefficient turns negative both in NLS and OLS models, although it is not significant. This is a suggestion that credit harmed firm growth in the 1990s, a question that is studied in Nkurunziza (2004).

Start-up Size and Growth: Both in 1992 and 1999, the convergence parameter is highly significant in the NLS model and start-up size has a negative and significant coefficient in OLS. The fact that start-up size has a significant impact on the rate of growth contradicts Gibrat's law of proportionate effect. Using the half-life measure to proxy for the dynamics to steady state, the findings suggest that it took firms eleven years to cover 50 percent of the gap between current and steady state size before 1992 while it took one year in the 1990s.[14]

There are two possible interpretations of the half-life figures. The first is that a high figure translates slow movement to steady state. The second interpretation is that a high figure shows opportunities of growth since firms starting closer to their steady state size will have lower growth opportunities. This latter interpretation seems to be consistent with the Kenyan case. Firms in the 1992 sample enjoyed higher growth opportunities than those in the 1999 sample.

By comparison, Evans (1987a) and Evans (1987b) propose an interpretation closer to the first case. He finds that American firms with an average age of four years and having sizes comparable with those in Kenya took nine years to move halfway through to their steady state. However, the half-life of firms with an average age of 10 years was about 21 years. Obviously, the comparability of the figures for Kenya and

[14] The half life of a firm's start-up size is given by $\ln 2/\beta$. For the derivation of the formulae, see Jones (2002: 10).

those for America is limited by the fact that they relate to two different economies analysed over different economic cycles.[15]

Age and Growth: Given the NLS estimation procedure, it is impossible to isolate the effect of age on firm growth using NLS results. However, OLS coefficients show that age was not significant in 1992 and that its net impact was positive in 1999, contradicting Jovanovic's model. However, we cannot draw conclusions on the basis of the OLS model given that it is not the right estimation procedure.

Other Controls: NLS results do not support the result that firms owned by Kenyans of African origin grow less than those owned by Kenyans of Indian origin but OLS results do. The NLS result is in accord with the finding by Aguilar and Kimuyu (2002) that ethnicity has no significant impact on firm growth in Kenya, although they use a different sample.

Despite the fact that simultaneity is addressed by using start-up access to credit, there may still be endogeneity due to unobserved heterogeneity at start-up. We instrument for credit at start-up using firm and owner characteristics as instruments.

[15] See Evans (1987a) and Evans (1987b) for a discussion of the period to which the American data relate.

Table 3: Instrumental Variable Estimation of Firm Growth
Dependent variable is annual growth rate in firm size

	Full Sample		1992 Sample	
	IV (2SLS)	**First-stage**	**IV (2SLS)**	**First-stage**
Bank loan at start-up	0.219**		0.303*	
	[0.042]		[0.169]	
Ln(start-up size)	-0.099***	-0.08***	-0.105***	0.116***
	[0.000]	[0.030]	[0.031]	[0.038]
Ln(age)	-0.015	0.171*	-0.176	0.217*
	[0.899]	[0.102]	[0.138]	[0.124]
Ln(age) squared	-0.005	-0.048*	0.028	-0.061**
	[0.838]	[0.026]	[0.031]	[0.031]
Kenyan of African origin	-0.129***	0.082	-0.108***	0.056
	[0.000]	[0.090]	[0.041]	[0.106]
Other ethnicity	-0.064	-0.002	-0.051	-0.031
	[0.178]	[0.113]	[0.060]	[0.128]
Textiles Sector	-0.045	0.140*	-0.083**	0.206**
	[0.181]	[0.076]	[0.044]	[0.093]
Food Sector	-0.027	0.157*	-0.084	0.177
	[0.472]	[0.097]	[0.057]	[0.117]
Metal Sector	0.045	0.057	0.045	0.134
	[0.336]	[0.076]	[0.057]	[0.096]
Owner has motor vehicle		0.132*		0.068
		[0.076]		[0.107]
Owner has real estate		0.086		0.106
		[0.067]		[0.083]
Owner has previous experience		0.008***		0.009**
		[0.003]		[0.004]
Firm is limited liability		0.074		0.126
		[0.78]		[0.099]
Constant	0.347**	-0.403***	0.521***	-0.449***
	[0.154]	[0.148]	[0.171]	[0.179]
R-squared (Uncentered)	0.25	0.28	0.28	0.37
Adjusted R-squared (Centred)	0.15	0.20	0.12	0.28
F-test of excluded instruments		3.64		2.33
		[0.008]		[0.06]
Hansen J-test of overidentification	2.479		1.978	
	[0.48]		[0.577]	
Number of observations	133	133	101	101

Numbers in brackets are White (1980) heteroskedasticity-consistent standard errors. Three, two and one star, correspond to 1 percent, 5 and 10 percent significance level, respectively. R-squared statistics are for the first stage regressions. Uncentered and centred R-squared are for the 2SLS regressions. Bracketed values for the F and J-statistics are *p-values*. Reference groups are Kenyan of Indian origin and wood for ethnicity and sector, respectively. The 1999 sample is excluded due to insufficient observations.

Four instruments are used to account for unobserved heterogeneity. Three of them relate to the owner and one to the firm. Whether an owner has a motor vehicle and real estate should be highly correlated with access to credit. Owning a car in Africa is perceived as a sign of prestige which may increase the perception of credit worthiness even when a motor vehicle cannot be used as collateral. An owner's past experience in the industry may suggest that the owner has built a reputation as a trustworthy borrower, so the variable should be positively correlated with credit use. Limited liability firms are dominant in the modern sector and hence have the highest probability of using bank loans.

Since information on firm specific characteristics is available only on firms managed by their owners, the sample size is reduced by half. How appropriate are the instruments? The F-test of excluded instruments rejects the null that the coefficients on the instruments in the first-stage regression are jointly equal to zero. Moreover, Hansen's J-test of overidentification does not reject the null that the set of instruments is appropriate. We, therefore, deduce that instrumentation for the credit variable is appropriate.

As in the NLS and OLS models of Table 2, access to credit and start-up size are significant with the expected signs. The positive coefficient of the credit variable confirms the results in Table 2 that firms that used credit at start-up grew faster than those that did not. The negative sign of the size variable suggests that firms tend to converge to their steady state. The age variable is not significant as in the OLS regression of Table 2. The reason may be that once start-up conditions are properly accounted for, age has no influence on the growth process. For instance, part of the impact of age on growth may be captured by access to credit if age is interpreted as a proxy for reputation, as suggested in Nkurunziza (2004).

One problem with the IV regression in Table 3 is that it estimates a linear model while we have already noted that NLS is the appropriate estimation. An alternative way of instrumenting credit and estimating NLS is to use the predicted values of the first-stage regression in Table 3 as an instrument of the credit variable. The results are reported in Table 4.

Table 4: Nonlinear Estimation of Growth Instrumenting Credit
Dependent variable is annual growth rate in firm size

	Full Sample	**1992 Sample**
Bank loan at start-up	4.04***	3.73***
	[1.33]	[1.01]
	(0.24)	(0.22)
β – *Parameter*	0.30***	0.40***
	[0.11]	[0.11]
Ln(start-up size)	-0.06	-0.06
Kenyan of Africa origin	0.31	0.47*
	[0.27]	[0.25]
Other ethnicity	-0.14	0.10
	[0.36]	[0.23]
Textiles sector	0.49	0.32
	[0.39]	[0.33]
Food sector	0.49	0.48*
	[0.34]	[0.28]
Metal Sector	1.13	0.75
	[0.70]	[0.64]
Constant	0.09***	0.08***
	[0.02]	[0.02]
R-squared	0.22	0.23
Adjusted R-squared	0.17	0.19
Log Likelihood	39.87	41.40
Number of observations	133	133

Numbers in brackets are White (1980) heteroskedasticity-consistent standard errors. Numbers in parentheses on the credit variables are adjusted from NLS estimates for comparison with OLS parameters. Three, two and one star, correspond to 1 percent, 5 and 10 percent significance level, respectively. The reference groups are Kenyans of Indian origin for ethnicity and wood for sector of activity.

As in the previous cases, the credit and start-up size variables are highly significant with the expected signs. The coefficients on credit are close to those derived in the IV model of Table 3 but they are double those of the NLS model in Table 2 where credit is not instrumented. The derived effect of start-up size in Table 4 is comparable with the value in Table 2. In summary, the qualitative results relating to the two variables of interest are comparable across the range of estimations reported in Tables 2 to 4.

The question is whether or not the IV estimation has improved the results of the OLS model and NLS models. The objective of estimating different models is to show whether NLS, IV, Fixed effects, GMM and Heckman are improvements over OLS. Focusing on the credit variable, we use a Hausman test to determine whether the difference between the coefficient of the OLS and alternative models is significant.[16] The test is specified as [Wooldridge (2002)]:

$$H = \left(\widehat{\gamma}_{ALT} - \widehat{\gamma}_{OLS}\right)' \left[\widehat{\sigma}^2_{\widehat{\gamma}_{ALT}} - \widehat{\sigma}^2_{\widehat{\gamma}_{OLS}}\right]^{-1} \left(\widehat{\gamma}_{ALT} - \widehat{\gamma}_{OLS}\right) \tag{6}$$

where H is the Hausman *t statistic*. The null is that the coefficient of the alternative model is not significantly different from the OLS coefficient. Therefore, rejection of the null implies that the alternative model is an improvement over the OLS specification whereas a failure to reject the null means that one should stick to the OLS estimates. The parameters $\widehat{\gamma}_{ALT}$ and $\widehat{\gamma}_{OLS}$ are estimated coefficients of the alternative and OLS models, respectively, while $\widehat{\sigma}^2_{\widehat{\gamma}_{ALT}}$ and $\widehat{\sigma}^2_{\widehat{\gamma}_{OLS}}$ are the respective variances of the coefficients. The Hausman test in equation (6) is equivalent to:

$$H = \frac{\left(\widehat{\gamma}_{ALT} - \widehat{\gamma}_{OLS}\right)}{\sqrt{\left[s.e\left(\widehat{\gamma}_{ALT}\right)\right]^2 - \left[s.e\left(\widehat{\gamma}_{OLS}\right)\right]^2}} \tag{7}$$

The *t-statistic* of the Hausman test that the credit coefficient of the IV regression is different from that of the OLS model is 4.30 and 1.45 for the full and 1992 models, respectively. The meaning is that IV improves on the OLS result when the full sample is

[16] Wooldridge (2002: 120) notes that "rather than comparing the OLS and 2SLS estimates of a particular linear combination of the parameters--as the original Hausman test does—it often makes sense to compare just the estimates of the parameter of interest." We focus on the coefficient of the credit variable.

used but there is no improvement on the 1992 sample. Since our focus is on the 1992 model, the conclusion is that the credit effect is not due to reverse causality or heterogeneity at start-up.

4. Credit, Growth and Convergence: Panel Data Analysis

Lagged credit and the instrumental variable approach pursued above do not address all the possible sources of endogeneity. There could still be endogeneity due to time-varying unobserved heterogeneity. For instance, a firm could borrow because it expects higher rates of growth in the future. In this case, expected growth determines credit use. Furthermore, we may need to deal with time invariant unobserved heterogeneity not captured by instrumental variable in Table 3.

In the first sub-section, we develop the methodology used to correct for endogeneity. The second sub-section presents the data used to estimate the growth model and the third sub-section discusses the empirical results.

4.1. Endogeneity and Panel Data Estimation

In the period from 1992 to 1994, we use fixed effects to solve the problem of endogeneity due to time invariant heterogeneity. This estimation approach wipes out the omitted variable bias if the omitted effects are time-invariant. However, as we discuss below, using fixed effects may introduce a new type of endogeneity when applied in the context of a model with a lagged dependent variable as an explanatory variable.

Endogeneity due to time varying factors not included in the estimation but correlated with both credit and growth are difficult to instrument since it is difficult to determine which time varying instruments may be correlated with access to credit but with no correlation to firm growth. With enough data points, this problem may be addressed through the use of a GMM estimator. The latter uses time varying appropriate lags and differences of exogenous independent variables that are used as internal instruments. GMM estimation provides also a framework to address the problem of endogeneity due to fixed effects estimation in models with lagged dependent variables.

The derivation of the fixed effects and the GMM estimator is sketched below. If all the firms are observed over the same time interval, the growth model in equation (4) simplifies to:

$$\ln\left(S_{i,t}\right)-\ln\left(S_{i,t-\tau}\right)=\theta\ln\left(S_{i,t-\tau}\right)+\gamma x_{it}+\mu_i+\nu_{i,t} \qquad (8)$$

where μ_i and $\upsilon_{i,t}$ are time-invariant and time-variant error components, respectively.[17] Normalising $\tau=1$, we have $\theta=-\left(1-e^{-\beta}\right)$ and $\gamma=\left(1-e^{-\beta}\right)$. The vector x contains all other variables explaining growth. The growth equation (8) is equivalent to:

$$\ln\left(S_{i,t}\right)=\theta^{*}\ln\left(S_{i,t-\tau}\right)+\gamma x_{i,t}+\mu_i+\nu_{i,t} \qquad (9)$$

where $\theta^{*}=(\theta+1)$. First differencing equation (9):

$$\Delta\ln\left(S_{i,t}\right)=\theta^{*}\Delta\ln\left(S_{i,t-1}\right)+\gamma\Delta x_{i,t}+\Delta\nu_{i,t} \qquad (10)$$

given that $\mu_{i,t}-\mu_{i,t-1}=0$. Estimation of equation (10) does not suffer from endogeneity due to time invariant heterogeneity since differencing wipes out time invariant effects. However, the method introduces a new endogeneity problem. By inspection, we see that $E\left(S_{i,t-1},\nu_{i,t-1}\right)\neq 0$ due to the relationship between $S_{i,t-1}$ and $\nu_{i,t-1}$ in equation (10). Therefore, estimating equation (10) by OLS produces biased estimates of θ^{*}. Nickell (1981) identifies three characteristics of the bias: (i) it is negative for positive values of θ^{*}; (ii) it increases with θ^{*}; and, (iii) it (slowly) decreases as sample size increases. The

[17] The term μ_i is also called unobserved effect, fixed effect, or unobserved heterogeneity. The time-variant error component is also referred to as idiosyncratic error. In equation (8), μ_i is a firm fixed effect.

second characteristic of the bias implies that OLS regressions of equation (10) may lead to a wrong conclusion of fast convergence.

In order to solve the problem of endogeneity introduced by first-differencing, Anderson and Hsiao (1982) propose the use of an instrumental variable approach that instruments $\Delta \ln\left(S_{i,t-1}\right)$ in equation (10). They suggest a vector of instruments $Z = [\ln\left(S_{i,t-2}\right), \Delta x_{i,t}]$ assuming that all variables in $\Delta x_{i,t}$ are exogenous. Building on Anderson and Hsiao's result that $\ln\left(S_{i,t-2}\right)$ is a good instrument, Arellano and Bond (1991) argue that if that is the case, then $\ln\left(S_{i,t-3}\right), \ln\left(S_{i,t-4}\right)..., \ln\left(S_{i,t-k}\right)$ are also good instruments, leading to the following moment restrictions:

$$E\left(\ln\left(S_{i,t-j}\right)\Delta v_{i,t}\right) = 0 \ \ for\ j = 2,3,....,(N-1) \tag{11}$$

and:

$$E(x_{i,t-k}\Delta v_{i,t}) = 0 \ \ for\ k = 1,2,3,....,(N-1) \tag{12}$$

when all variables in x are exogenous. In our case, since credit is assumed to be endogenous, equation (12) becomes:

$$E(x_{i,t-k}\Delta v_{i,t}) = 0 \ \ for\ k = 2,3,4,....,(N-1) \tag{13}$$

Equations (11)-(13) show that there may be more valid instruments than endogenous variables. In order to combine the instruments efficiently, Arellano and Bond propose the use of Hansen (1982) Generalised Method of Moment (GMM) estimator. It is computed in two steps. First, all the instruments are concatenated in a single vector:

$$Z^* = \left[\ln\left(S_{t-2}\right), \ln\left(S_{t-3}\right), ..., \Delta x_{t-1}, \Delta x_{t-2}, \Delta x_{t-3}, ...\right] \tag{14}$$

Then, the inverse of the variance-covariance matrix of the instruments denoted A_H, is computed to combine them efficiently and then used to derive the GMM estimator:

$$\hat{\delta}_{GMM} = (X'Z^* A_H Z^{*\prime} X)^{-1} X'Z^* A_H Z^{*\prime} y \tag{15}$$

The main advantage of the GMM over the Anderson Hsiao instrumental variable estimator is that it is efficient (albeit asymptotically) as it uses more moment restrictions than the latter. In addition, if any of the variables in $x_{i,t}$ is endogenous, appropriate instruments can be found using pre-determined and exogenous variables within the system. The fact that internal instruments are available to help resolve the problem of endogenous explanatory variables makes GMM an appealing estimation method.

4.2. Descriptive Statistics and Construction of the Variables

We first present and discuss the descriptive statistics covering the period 1992 to 1994.

Table 5: Descriptive Statistics for models Using 1992-1994 Data

Variables	Mean	Standard Deviation	Observations
Growth Rate	-0.02	0.64	360
Ln Size	2.82	1.69	588
Ln lagged Size	2.82	1.71	418
Ln age	2.67	0.80	588
Ln age squared	7.76	3.93	588
Loan use	0.25	0.43	498
Lag loan use	0.20	0.40	361
Has overdraft	0.60	0.49	584
Lag has overdraft	0.61	0.49	415
Kenyan of African origin	0.43	0.49	588
Kenyan of Indian origin	0.51	0.50	588
Other Ethnicity	0.07	0.25	588
Textiles sector	0.24	0.43	588
Food sector	0.22	0.41	588
Metal sector	0.26	0.44	588
Wood sector	0.28	0.45	588
Mombasa region	0.17	0.38	588
Nakuru region	0.09	0.29	588
Eldoret region	0.09	0.29	588
Nairobi region	0.64	0.48	588

These data have the advantage of allowing growth rates calculated on equal periods. The disadvantage of the data is that they cover only a short period of three years between 1992 and 1994. Despite this limitation, the nature of the sample allows the estimation of dynamic models that is impossible with the Pre-1992 sample. Hence, the results of the models in the two sub-samples should be seen as complementary.

In the post-1992 period, the construction of the loan variable is as follows. The variable takes value one when a firm has a positive balance on loans. Given that the variable has many missing values, the following sequence explains how they are treated. The variable takes value 1 if a firm did not apply for a loan in the last year because it was already in debt. The value is zero when a firm claims it has never used a loan. The value is also zero if a firm has not operated a current account. The variable takes value zero also if a firm claimed it did not apply for a loan because it did not need one. Then, as we are interested in the use of past loans, any firm with value 1 in a year is given 1s in all subsequent years. Conversely, any firm with a zero in a year is given zeros in all previous years. Finally, whenever there is a missing value corresponding with a year where the balance on loans is zero, the missing is changed into a zero. Loans used before 1992 are not specifically considered unless they were still being serviced in 1992. Table 4.6 gives a snapshot of the logic underlying the construction of the credit variable.

Table 6: Construction of the Loan Dummy Variable (t is current year)

Indicator Variables	Loan Dummy Variable
Positive current balance on loans	1
No new loan because already in debt	1
Never borrowed	0
Never had a current account	0
Not applied because no need for a loan	0
If loan dummy is 1 at time t	1 in all following years
If loan dummy is 0 at time t	0 in all previous years
Balance on loans is zero	0

The Overdraft credit variable takes value 1 if a firm has access to overdrafts and zero otherwise.

The other explanatory variables are size measured as the log of the number of full time workers. Six observations that had no data on the number of full time workers were replaced by the total number of workers. Age indicates the number of years since firm creation. Sectoral dummy variables are added to control for sectoral effects. About ten firms were recorded in different sectors in different waves. To correct for the inconsistencies, a firm coded several times in a sector but only once in another sector was given the code that came more frequently. When a firm was coded once in a sector and once in a different sector, we kept the latest coding as we realised that most errors on this variable were in the earlier waves.[18]

[18] The data on ethnicity was only available in 1992 and 1999. To fill the gaps in 1993 and 1994, we assumed that ownership did not change over the period so a firm that had data on ethnic status of the owner in 1992 kept the same status throughout the sample period. Similarly, for a firm that had no information on ethnicity status in 1992 but had information in 1999, we used the latter to fill the gaps. Finally, a few firms that had no information in either year are in a third category called 'Other ethnicity'. This third group comprises also the few firms owned by individuals from other ethnic backgrounds. These are non-Kenyans and Kenyans of Middle Eastern origin.

4.3. Empirical Results

The results of OLS, fixed effects and GMM are compared in the following table.

Table 7: OLS, Fixed Effects and GMM Models of Firm Growth: 1992-1994

	OLS Equation (9)	**Fixed Effects Equation (10)**	**GMM (1) Equation (15)**	**GMM (2) Equation (15)**
Lag of loan use	0.212**	0.485***	0.658***	0.640***
	[0.093]	[0.164]	[0.229]	[0.228]
Lag of overdraft use	0.112	0.168	0.318*	0.178*
	[0.112]	[0.144]	[0.185]	[0.133]
Loan use (level)			-0.009	
			[0.166]	
Overdraft use (level)			0.503**	
			[0.248]	
Lagged log size	0.811***	-0.297***	0.086	0.041
	[0.035]	[0.071]	[0.211]	[0.189]
Log age	0.170	-0.613	-0.803	-1.215
	[0.264]	[0.422]	[0.889]	[0.914]
Log age squared	-0.026			
	[0.049]			
Kenyan of African origin	-0.030			
	[0.107]			
Other ethnicity	0.120			
	[0.129]			
Textiles sector	0.076			
	[0.094]			
Food sector	0.152			
	[0.110]			
Metal sector	0.091			
	[0.101]			
Constant	0.095	5.065***	0.058	0.060
	[0.348]	[1.135]	[0.106]	[0.096]
R-squared	0.86	0.53		
R-squared within		0.23		
F-statistic	190.04***	9.38***	1.96*	3.16*
Observations	315	315	117	122

Numbers in brackets are White heteroskedasticity-consistent standard errors. Three, two and one star, correspond to 1 percent, 5 and 10 percent significance level, respectively. The reference groups are Kenyan of Indian origin and wood for ethnicity and sector of activity, respectively.

No test for overidentifying restrictions is reported for the GMM model because it is not overidentified. The reason is that of the 3 data points available, two are used to lag and first-difference the variables so instrumentation uses one cross-section.[19] Fixed effects and GMM estimations control for heterogeneity and simultaneity. Therefore, the positive sign and significance of the loan variable suggest that the importance of the effect of loans on firm growth is not due to endogeneity.

[19] This also explains the small samples used for the GMM models. Arellano and Bond (1991) lose three cross-sections as they estimate models with a maximum of two lags.

There is a notable increase in the coefficient and the significance of the lag of loan use when we move from the OLS to the fixed effects model. This appears to imply a negative correlation between the fixed effects and loan use. One explanation may be that, on average, firms with a high fixed effect have a lower likelihood of using loans. This could be the case when the fixed effect reflects firm characteristics such as the quality of management that enables a firm to use its internal resources more efficiently, implying less reliance on loans.

It is relevant to note that controlling for endogeneity, there is no evidence of convergence in the period 1992-1994, confirming the result found by Teal (1999) using Ghanaian data.

Using the Hausman test to compare the loan coefficient over the four models in Table 4.7, none of the alternative estimations seems to be an improvement over the OLS estimate. *The t-statistic* of the Hausman test of the fixed effects against OLS is 1.68, suggesting that we cannot reject the null that the Fixed effects and OLS coefficients are equal. Similarly, comparing OLS and GMM coefficients, the *t-statistics* are 1.09 for both versions of the model, suggesting that the two coefficients are statistically the same.

5. Credit, Growth and Selectivity Bias

Potential selection bias is the last issue we address. Although the literature on firm growth usually ignores the potential problem of self-selection, selection bias may arise from the fact that growth analysis is only carried out on a sub-sample of surviving firms. If survival is not random, the results of the growth model will be biased. Mansfield (1962) conjectures that the negative growth-size relationship uncovered in empirical studies is the result of slowly growing firms exiting. Accordingly, entry and exit should be integrated in the analysis of growth to correct for this potential bias. However, in practice, failures are omitted from the sample and analysing firm dynamics based on surviving firms does not necessarily introduce a significant bias [Jovanovic (1982)].

Many studies, including some in Africa, have tested for the bias due to self-selection and found it non-significant. In his study of medium and small enterprises in Botswana, Lesotho, South Africa, Swaziland and Zimbabwe, McPherson (1996) tests for the sample selection bias for Swaziland and Zimbabwe. He finds that sample selection is non-significant. Evans (1987a) and Evans (1987b), using data on American small businesses finds a similar result.

Atkinson, *et al.* (1992) refer to a number of studies using the Michigan University Panel Study of Income Dynamics (PSID) that have found no significant selection bias. Using data on the period 1992-1994 we test for the significance of the selection bias applying a Heckman Full Information Maximum Likelihood (FIML) method. This method estimates an OLS-type regression of firm growth conditional on a selection equation determining whether or not a firm is observed. A selection bias is significant when the process driving growth is related to the process driving firm exit, measured by the correlation between the residuals from the two equations.[20] Table 8 reports the estimation results.

[20] An alternative method of determining the significance of the selection bias is to include the Inverse Mills Ratio (IMR) from the selection equation into a growth equation. Since IMR measures the extent of the selection bias for each observation, the significance of its coefficient in the growth equation indicates a significant selection bias.

Table 8: Heckman FIML Selection Model of Firm Growth: 1992-1994

Dependent variable is Ln of current size for the regression equation and the probability that a firm is observed in any year during the sample period for the selection equation.

	OLS Equation	Regression Equation	Selection Equation
Lag of loan use	0.212**	4.501***	-0.657***
	[0.093]	[0.572]	[0.233]
Lag of overdraft use	0.112	0.308	0.477*
	[0.112]	[0.294]	[0.244]
Lagged size	0.811***	0.610***	0.087
	[0.035]	[0.206]	[0.064]
Log of Age	0.170	-1.147	0.237*
	[0.264]	[1.305]	[0.124]
Log of Age squared	-0.026	0.250	
	[0.049]	[0.255]	
Kenyan of African origin	-0.030	0.573	0.334
	[0.107]	[0.467]	[0.241]
Other ethnicity	0.120	2.582***	-0.492*
	[0.129]	[0.592]	[0.285]
Textiles sector	0.076		0.308
	[0.094]		[0.233]
Food Sector	0.152		0.364
	[0.110]		[0.251]
Metal Sector	0.091		0.328
	[0.101]		[0.205]
Dummy for year 1993			1.424***
			[0.173]
Constant	0.095	1.530	-1.572***
	[0.348]	[1.571]	[0.461]
Log pseudo-likelihood			-173.101
$Wald-\chi^2$			561.56***
ρ			-0.997***
$\chi^2(1)-test$ of $\rho=0$			4.69**
			[0.030]
R-squared	0.86		
F-statistic	190.04***		
Observations	315	315	315

Numbers in brackets are robust White heteroskedasticity-consistent standard errors. Three, two and one star, correspond to 1 percent, 5 and 10 percent significance level, respectively. The reference groups for ethnicity and sector of activity are Kenyan of Indian origin and wood sector, respectively. The bracketed value under the $\chi^2(1)$ *test* of $\rho=0$ is a *p-value*.

The sectoral and time dummies are introduced in the selection equation to model the probability that a firm is observed in any given year. As Nkurunziza (2004) discusses in more details, firm failures tend to be sector-specific, hence motivating the introduction of the sectoral dummies in the selection equation. These variables are not significant in the regression equation but they are in the selection equation (The metal sector is significant at 10 percent level). With respect to the 1993 dummy variable, it captures the effect of the policy shocks that hit the Kenyan economy. They were most profound in 1993.

The value of the $\chi^2(1)$ statistic of the $\rho - test$ of independence of the regression and selection equations is 4.69 with a *p-value* of 0.03. The null of independence between the two regressions is rejected, implying that the growth model and the selection equation must be estimated simultaneously. However, although self-selection is statistically significant, the positive sign and high significance of the loan variable in the growth equation of the Heckman model mean that the effect of credit on firm growth is not due to a selection bias, strengthening the results from previous models.

If anything, the effect of credit on firm growth is larger when the selection bias is controlled for. The fact that ρ is negative and highly significant combined with the finding that the effect of credit on firm survival is negative and highly significant imply that conditional on firm survival, the effect of credit on firm growth is positive. In terms of magnitude, the Heckman model produces the highest coefficient of all the models we have estimated.

5. Conclusion

All the models suggest that conditional on firm survival, access to credit increases firm growth. This result is robust to several estimations and different sample periods. The instrumental variable approach is used to control for endogeneity using data covering the period from firm creation to the first time a firm was interviewed in 1992 or 1999. The findings show that the positive effect of credit on firm growth is not due to endogeneity. For the period between 1992 and 1994, fixed effects and GMM panel data estimation techniques produce a similar result.

The finding from a Heckman FIML estimation used to control for a potential selection bias finds that the bias is significant but that the effect of credit on firm growth, conditional on survival, is even stronger. These findings lend support to the hypothesis that the lack of access to credit may be an important impediment to firm growth as claimed by firm managers in Kenya.

In many models, initial size is negative and significant, supporting the convergence hypothesis but, at the same time, contradicting Gibrat's Law of proportionate effect. The fact that age is weakly related to growth in most models suggests that the variable may not proxy for efficiency as suggested by Jovanovic. The impact of the variable on firm growth may be through reputation and hence the credit variables. Indeed, in models excluding the credit variables, the age coefficient increases and becomes significant in some of them.

In summary, we have responded to the two questions raised at the beginning of the paper. Firstly, access to credit appears to be an important determinant of firm growth, supporting the claim made by business leaders in Kenya. Secondly, there is evidence that initial size is an important determinant of firm growth in line with the convergence hypothesis but in contradiction with Gibrat's law.

Among the issues the paper has not explored, the following three are worth noting. The impact of age and credit on firm growth could be through productivity. Are growing firms those that can borrow and invest into better technologies? Secondly, the study of growth over the 1990s needs to be complemented by analysis of firm resilience given that the 1990s was a period of economic crisis. This question is tackled in Nkurunziza (2004). Thirdly, the paper focused on the behaviour of firm size out of equilibrium. An equally relevant issue is the unconditional distribution of size where the short term transients have lost influence. This question is analysed in Nkurunziza (2004) on firm mobility, using a novel methodology based on a Markov chain.

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