Determinants of African Manufacturing Investment: 
the Microeconomic Evidence

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In this survey paper we consider the microeconomic evidence on investment in African manufacturing. We analyse both the determinants of investment behaviour and the return to that investment. In the 1990s market selection — the process by which the capital stock is reallocated in favour of more efficient firms — has been as strong in Africa as elsewhere. While the macroeconomic literature has focused on low returns to investment as an explanation for Africa’s poor growth performance, the micro-data indicate high potential returns. However, investment rates remain quite low, presumably as a result of risk, but the surveys currently available are not suitable for testing this.

1. Introduction

Many observers have attributed Africa’s poor economic performance to the low investment rates typical of most African countries. The growth regressions literature finds cross-country evidence for a link from investment to growth (Collier and Gunning, 1999). This is supported by time-series evidence for individual countries. For example, Ghura (1999) finds for Cameroon for 1963–96 that the effect of changes in private investment on economic growth is robust, large and significant. Clearly, if African economic growth is low because of low investment rates then this simply shifts the question: why are investment rates so low? Some answers are suggested by time-series studies, using aggregate data. For example, Jenkins’s (1998) time series analysis for Zimbabwe (using macro-data) finds that ‘in the long run, investment is constrained by the availability of finance, especially retained profits’ (p. 34). However, firm-level data suggest that financial constraints are relatively unimportant (Bigsten et al., 1999a; Fafchamps and Oostendorp, 1999). Other studies using aggregate data stress risk, rather than financial constraints, in particular the negative effect of
political instability on investment. For example, Gyimah-Brempong and Traynor (1999) find a bi-directional relationship between political instability and economic growth: ‘slow economic growth leads to political instability which in turn leads to further economic stagnation’ (p. 80).

Devarajan et al. (1999) challenge the view that the rate of investment in Sub-Saharan Africa is too low. Africa’s growth problem, they suggest, may rather be that the productivity of investment is too low, which in turn might explain the low saving and investment rates. Using cross-country regression, they find that neither private nor public investment has had significant influence on GDP growth. They then analyse the productivity of manufacturing investment in Tanzania over a 25 year period to find that ‘public policies, insulation from market forces, weak technological capacity [have] all combined to render manufacturing capital in Tanzania unproductive’. Assuming that Tanzania is representative enough of the region in the present context, the low productivity of capital may then explain the absence of correlation between investment and growth in cross-country regressions.

The focus of this paper is on the microeconomic evidence regarding the rate and productivity of investment. Until very recently micro-econometric analyses of investment in manufacturing were infeasible because of the absence of firm-level panel data. Data availability has been transformed in the 1990s, particularly as a result of the World Bank’s Regional Programme on Enterprise Development (RPED). RPED surveys have been conducted in eight African countries: Burundi, Cameroon, Côte d’Ivoire, Ghana, Kenya, Tanzania, Zambia and Zimbabwe. In each country a sample of ~200 firms was interviewed in three consecutive years. Very similar surveys have been conducted in Ethiopia and Uganda. These surveys are comparable across countries and this feature has been exploited by the ISA (Industrial Surveys in Africa) group (see, e.g., Bigsten et al., 1998, 1999a,b, 2000). The fact that major reforms took place on a regional scale in Africa only beginning with the late 1980s makes the task of drawing policy conclusions from cross-country regression based on a sample dominated by observations from earlier periods a delicate exercise. On the other hand, the survey data we draw on have all been collected since 1992 with similar methodology, and on business units that seem to have faced quite similar technological settings and policy environments. This paper draws heavily on these new surveys. We should stress that
the set of firm-level surveys is still quite small. Whether the results from countries reported in Sections 2 and 3 generalize to other African countries remains to be seen. We consider this a key research priority.

The surveys suggest two stylised facts about investment in Africa. The first is well known: there is very little of it. Indeed, pooling the RPED surveys for Cameroon, Ghana, Kenya and Zimbabwe, Bigsten et al. (1999a) find a median rate of investment \((I/K)\) which is virtually zero. The other fact is not well known: African manufacturing firms are highly profitable.

The link between investment and profitability is one way of looking at whether the productivity of investment is too low in Africa. A second way is to examine whether African markets ‘tolerate’ inefficient producers or poor investment, that is, to look at the strength of market selection in Africa compared with what we find elsewhere. By market selection we mean the process by which capital stock is reallocated from less efficient producers to more productive ones through producer turnovers and differential investment or growth rates by firms in the same industry. If selection is too weak — say, because incumbents are protected from foreign and domestic competition — then too much investment will be made by inefficient producers. This in turn will reduce the productivity of capital stock as an industry- or economy-wide aggregate. However, again the available survey evidence suggests that the process of market selection has probably been as strong in Africa as anywhere else in the 1990s. Firms do vary significantly in productivity within the same industry but, at the same time, we also observe a process of reallocation of capital stock from less productive units to more productive establishments.

The structure of the paper is as follows. Section 2 reviews the main models of market selection, looks at empirical tests of some of their implications in developed and middle-income economies, and then presents the African evidence. In the review of the theoretical literature we emphasise the allocative function of market selection and the link between models of selection and conventional models of investment. All models of market selection are theories of investment. They differ from conventional or representative-firm models in that their focus is technological heterogeneity as a determinant of inter-firm differences in investment decisions. In Section 3, we present results of the estimation of standard investment equations. We summarise and conclude in Section 4.
2. Productivity, Growth and Market Selection

Industrial census data sets from developed and developing countries alike indicate that competitive industries are always in states of autonomous flux. Even in the absence of changes in relative prices, firms continually enter an industry at the same time as others leave. And the typical picture among incumbents is not of uniform growth or decline but, rather, one in which some expand while others contract. This is a phenomenon that models based on the representative-firm formulation sidestep in order to focus on the interaction of inter-industry flows with changes in economy-wide parameters. In this section we will first briefly describe the main models of market selection that seek to explain it. We shall then summarise results of empirical tests of some of their implications on data sets from developed and middle-income economies, after which we will look at the evidence from Africa. By models of market selection we mean models of competitive supply which portray the facts of simultaneous entry and exit and disparities in growth performance as outcomes of intra-industry reallocation of resources from less productive or efficient producers to more efficient ones. The models reviewed below have all been developed within the last 20 years. However, they formally establish a very old conventional wisdom in economics, namely, the notion that, because only the ‘fittest’ survive it, greater competition is a source of productivity gains at the level of the individual industry. They therefore constitute an important component of the theoretical rationale for liberal trade policies and industrial deregulation. Not as obvious, but no less important, is the implication of selection models for the determination of firm-level investment. If a firm makes its exit or expansion decisions based on its perceived relative productivity, then its rate of firm investment must depend on past productivity. This means that more productive firms must have higher investment in a cross section, not only because higher investment leads to higher productivity, but also because causality flows in the opposite direction.

2.1 Models of Market Selection

Models of market selection assume the technological heterogeneity of producers. Thus, Lucas (1978) uses permanent inter-firm productivity differentials as the basis for a theory of the size distribution of firms and attributes them to inter-firm differences in management talent.
Lippman and Rumelt (1982) suggest that productivity differentials of the sort that generate results of the Lucas model need not be traced to differences in management ability. They can arise from the fact that the imitation of production techniques is usually imperfect because of the existence of functionally unique, unobservable or indivisible factors of production, of which ‘management ability’ is only one. In Hopenhayn (1992), productivity differences persist because competitive advantages that some firms might have acquired as a matter of historical accident fail to decay quickly enough. In Jovanovic and Macdonald (1994), perfect imitation is possible but productivity differences endure nonetheless because imitation is costly and takes time. In Pakes and Ericsson (1989), firms differ in productivity because of differences in their investment in process-improving innovations, which, presumably, can in turn be traced to differences in more fundamental characteristics such as ‘management ability’ and attitude to risk.

A second common feature of models of selection is the existence of a threshold level of productivity defining the point of equilibrium entry into and exit from an industry. The significance of this is that economy-wide changes in relative prices that shift up the threshold prompt a process of selection through which the less productive are forced to exit at the same time as new entries occur by outsiders which happen to meet the higher productivity requirement. Whether or not selection would also take place even in the absence of relative price changes depends on the source of productivity differences or on the assumptions made about each firm’s knowledge of the same differences. Autonomous selection is ruled out if firms cannot invest in the improvement of productivity, and each firm knows the true magnitude of its relative productivity. This is the case with the models due to Lucas (1978) and Lippman and Rumelt (1982). Although productivity differentials lead to greater variation in firm size in both of these models, they fail to translate into inter-firm differences in growth performance because of the assumption that each firm knows its position in the productivity spectrum. In practice, it takes time and experience for a firm to learn about the full extent of its competitive advantage, even if it could not actively invest in its improvement. In what is probably the best known theory of competitive selection, Jovanovic (1982) models this process of ‘passive learning’.

As in the models of Lucas (1978) and Lippman and Rumelt (1982), technological heterogeneity is captured in the Jovanovic model as Hicks-neutral inter-firm differences in productive efficiency. Each
potential entrant and incumbent, \( z \), of an industry is assumed to face a common production function, \( f(.) \), multiplied by a strictly positive transformation, \( \xi(.) \) of a random error composed of two components, \( \theta_i \) and \( \omega_{it} \), of which the first is the true relative productivity index of the firm while the second registers a purely temporary, zero-mean and homoscedastic random productivity shock. Firm \( i \)'s technology can then be described as

\[
Q_{it} = f(z_{it}, \beta)\xi(\theta_i + \omega_{it})
\]

where \( z_{it} \) is a vector of observable inputs, \( \beta \) is a vector of parameters and \( f \) is strictly concave in each element of \( z_{it} \). In Lucas (1978) and Lippman and Rumelt (1982), \( i \) knows the value of \( \theta_i \) prior to or upon entering the given industry. The firm will have decided on entry if this value was at least as high as some critical magnitude \( \theta^* \) given the cost of entry and the value of entry current product and factor prices imply, and will operate at a scale proportional to \( \theta_i \). In contrast, the firm never knows the true value of \( \theta_i \) in Jovanovic (1982). It does know, however, the distribution from which the true value is drawn, as well as the exact forms of \( f \) and \( \xi \). Its entry decision will have therefore been based on an estimate. Once in the industry, the firm continually updates this estimate on the basis of the latest productivity shocks. Among members of an entry cohort, those for which \( \theta \geq \theta^* \) experience positive productivity shocks, survive and expand as they revise up the estimate \( x \) with greater and greater precision. At the same time bad productivity shock induces firms for which \( \theta < \theta^* \) to progressively contract and eventually exit the industry. The process continues until surviving members of the entry cohort reach an age of maturity by which attrition will almost have ceased since survivors will have discovered the true magnitude of their productivity more or less fully. The variance of productivity and the rate of growth also diminish as the cohort ages. A consequence of this is that a cross section of firms across age groups should reveal an inverse relationship between the age of the firm and the expectation and variance of its growth. On the other hand, the level of productivity and the probability of the firm’s survival should be positively correlated with firm age. Similarly, a cross section of firms across size groups should exhibit an inverse relationship between the size of a firm and the expectation and variance of its growth rate while the productivity of the firm should be positively correlated with the firm’s size, as should its probability of survival.
The age effects just described are all distinctive implications of passive learning. So is the effect of firm size on the variance of the firm’s growth rate. However, the same cannot be said of size effects in productivity, the expected growth rate or the probability of survival. Of these, size effects in productivity are the least interesting since they can have a range of possible sources, including economies of scale and any kind of technological heterogeneity of producers. A negative size effect on the expected growth rate of a firm can also arise from a variety of sources. Again, economies of scale is one source. Jovanovic and Macdonald (1994) show that it can also arise from competitive diffusion under certain assumptions, including that imitation is costly, that all firms sample from the same pool of techniques and that the elasticity of supply is independent of firm size. Finally, the expected growth rate of a firm also decreases with the firm’s size in Hopenhayn’s model because of the gradual decay of initial productivity premiums.

Size effects in the probability of a firm’s survival are more distinctive, but they too have at least one possible source other than passive learning. As Pakes and Ericsson (1989) show, they can also arise from competitive investment in the improvement of productivity. In a separate category of its own among models of market selection is that of Nelson and Winter (1978). This is a model of ‘active learning’, as is that of Pakes and Ericsson, in that inter-firm differences in productivity are outcomes of different rates of investment in the improvement of techniques. Unlike the models considered so far, however, the Nelson–Winter model is not one of competitive selection. Each producer is assumed here to behave monopolistically and differs from others in the magnitude of its perceived market power. A second feature of the model is that each producer is liquidity constrained and makes its production and investment decisions under bounded rationality. Depending on the assessment of its market power, each firm sets its target mark-up, which then governs current production and investment decisions. However, the firm is not seeking to maximize its net present value in making those decisions since it is assumed not to know the production frontier of the industry in which it is operating. It nonetheless invests in productivity improvement in the belief that technology can always be improved upon to reduce costs no matter its current state. Although the return to such investment in terms of actual productivity gains is always uncertain, productivity does increase stochastically with the level of the investment...
made. That the investment is subject to a financing constraint means that its level increases with a firm’s size since the larger a firm is, the greater its market share, and hence the greater its ability to finance investments externally or out of profits. However, greater market share also means a higher mark-up rate to defend and, hence, lower incentive for productivity improvement. Indeed, a successful firm must sooner or later attain a critical size beyond which the desire to protect its mark-up rate outweighs gains from improvement in productivity. The result is that the investment in productivity improvement rises with a firm’s size initially but has to decline or flatten out eventually. This pattern is reflected in a nonlinear size effect in growth whereby the expectation and variance of firm growth both increase with the size of the firm before eventually flattening out or declining. Since the effect of investment in productivity improvement on firm size accumulates over time, the size effect in the firm’s growth rate should be mirrored by an age effect whereby the expectation and variance of growth are concave in the firm’s age. However, this is a spurious age effect since it should disappear once we control for firm size.

2.2 Evidence from Developed and Middle-income Economies

Empirical evidence relating to market selection has so far taken one of three forms. The first type consists of results of studies testing for age and size effects in producer entry, exit and growth. We will refer to this as the ‘growth-turnover’ evidence. The second is what we may call the ‘productivity-turnover’ evidence, by which we mean findings of studies comparing the relative productivity of new entrants, incumbents and exits in relation to an industry or to export markets. Evidence in this category is in the form of testing the assumption of models of market selection that there are permanent inter-firm differences in productivity and that new entries and exits must come from the lower end of the productivity distribution. We finally have ‘productivity-reallocation evidence’, that is, findings of studies testing whether or not there is a process of reallocation of resources from less productive to more productive firms over time in individual industries or sectors. Studies providing evidence in the ‘growth-turnover’ category test the implications of models of market selection while those providing evidence in the other two categories test their premises. The three sets of evidence are therefore complementary. Thus, while
detecting age or size effects in the dynamics of firms enables us to maintain the hypothesis of selection driven by inherent inter-firm differences in productivity as a null, it will never enable us to rule out other sources of the same effects. On the other hand, it is obvious from the multiplicity of models of selection that a given distribution of firms by productivity is consistent with a variety of patterns of selection depending on the assumption we make regarding the individual firm’s knowledge of its position on the productivity spectrum. And the only way that one can verify such an assumption is by testing their implications.

Major studies reporting evidence in the ‘growth-turnover’ category include Evans (1987a), Hall (1987) and Dunne et al. (1989a,b) on large-scale US data sets and Dunne and Hughes (1994) on a British data set. These all share the finding that, although the probability of survival of a firm increases with the firm’s initial size, the expected rate of firm growth is smaller the higher the initial firm size. With the exception of Hall, the same studies also report a negative relationship between initial firm age and the expected rate of firm growth but a positive relationship between the probability of a firm’s survival and its initial age. The first set of findings supports the implications of every model of competitive selection while the second is evidence for the presence of a passive learning phase in the life cycle of firms. Both sets of findings are evidence that market selection is an important element of the force driving the dynamics of firms and, hence, the evolution of industries. Neither set tells us, however, how important selection effects are relative to industry effects in the reallocation of resources observed in an economy over a period of time. The study by Dunne et al. and two other US-based studies, namely, Leonard (1987) and Davis and Haltiwanger (1992), find that the volume of resources involved in the intra-industry reallocation of resources through selection effects is at least as large as that of inter-industry flows.

At least two studies provide evidence in the ‘productivity-turnover’ category based on US data sets. Having analysed total factor productivity in US manufacturing plants over the period 1972–87, Baily et al. (1992) find significant firm fixed effects over a 10 year period. Productivity is also lower, on average, in new entries to and exits from an industry than in establishments continuing operation. In a somewhat different but no less relevant context, Bernard and Jensen (1999) report that exporters are more productive than non-exporters, while productivity increases with the level of exports among exporters. This
and their finding that causality flows from productivity to exporting status and not vice versa suggest the existence of a threshold level productivity defining the point of entry and exit from the market. Indeed, they find that while new entries into the export market will have experienced growth in productivity in the period immediately preceding entry, firms leaving the export market will have experienced significant falls in productivity prior to the point of exit. Bernard and Jensen also find that established exporters are, on average, more productive than firms that have newly entered the export market, which are in turn more productive than firms that have left the export market or never joined it in the first place.

Similar evidence has been reported by several authors for middle-income countries. Liu (1993) finds in Chilean manufacturing census data for 1980–6 that technical efficiency is higher for new entries than exits, while the average technical efficiency of new entries is lower than that of incumbents. Liu and Tybout (1996) find a similar result for selected industries in Colombia for the period 1979–80. Based on the analysis of census data of the 1980s from Korea and Taiwan, Aw et al. (1999) report results very close to those of Bernard and Jensen for the USA. In both the Taiwan and the Korean data sets, plants that diversify into export market are those which have had higher total factor productivity than others just before starting to export. Total factor productivity is also higher on the average for established and continuing exporters than for new entries, which, in turn, have higher productivity than exits or non-exporters. Similar results are reported by Clerides et al. (1998) based on data from Columbia, Mexico and Morocco.

Evidence in the ‘productivity-reallocation’ category is reported by some of the studies already cited. Thus Baily et al. find that the reallocation of output from less productive firms to more productive firms is an important source of industry-wide productivity in US manufacturing. Similarly, Bernard and Jensen (1999) attribute >40% of the growth total factor productivity to the same source for the period 1983–92.

The evidence from middle-income countries is rather mixed. For example, Pavcnik (2000) finds that the reallocation of output from less productive to more productive firms accounted for nearly 70% of the growth of total factor productivity in Chilean manufacturing during 1980–6, while Liu and Tybout (1996) find no evidence of such reallocation in Colombian industry for roughly the same period.
2.3 The African Evidence on Firm Growth and Market Selection

There are no studies of firm dynamics based on industrial census data from African economies. However, the studies by Mengistae (1998) and Ramachandran and Shah (1999), both based on manufacturing sample survey data, show that the same forces of market selection reported elsewhere are also very much at work in industries in Africa. The evidence in these papers falls in the ‘growth-turnover’ category. In particular, Mengistae (1998) finds that smaller firms grow faster controlling for initial firm age, while younger firms grow faster controlling for initial size.\(^1\) The finding is based on an analysis of data from the Ethiopian Industrial Enterprise Survey. This survey took place in two waves and was quite similar in design to the World Bank’s RPED survey programme. It was a joint undertaking of the Department of Economics of the Addis Ababa University, the Centre for the Study of African Economies, Oxford, and the Free University of Amsterdam. The first wave was implemented in September–October 1993 and covered 220 firms in mainly six industries. The second wave revisited 180 of these and covered a further fifty-four firms. The results on firm growth and productivity as summarised below are based on the analysis of returns of the first wave. We report in Tables 1 and 2 results of fitting the augmented Gibrat equation by ordinary least squares to the 1993 wave of the Ethiopian data. Gibrat’s equation relates the current or end-of-period size of a firm, \(S_t\), to its beginning-of-period size, \(S_{t-\delta}\), and a set of controls including its beginning-of-period age, \(A_{t-\delta}\), and can be written in the log linear form as:

\[
\ln S_t = \alpha + \beta \ln S_{t-\delta} + \gamma \ln A_{t-\delta} + \sum_{j=1}^{k} \lambda_j Z_j + \varepsilon_j
\]

\(^1\) Ramachandran and Shah (1999) show that smaller firms grow faster based on an RPED sample pooled across four countries. However, unlike that of Mengistae (1998), their result is not strictly comparable with those in the literature on firm growth in developed economies. This is because they measure the growth performance of firms from start-up to the present. Because firms start up at different points in time, this means that they compare growth as observed over different time intervals. In contrast, growth is compared over the same time interval in the standard business growth equation. The significance of this is that, while we can interpret age effects as some kind of life cycle effect in the standard growth equation, the coefficient of the age variable in the equation used by Ramachandran and Shah will necessarily be a mixture of start-up time effects and lifetime effects.
where $\alpha$, $\beta$, $\gamma$ and $\lambda_j$ are all constants, $Z_j$s are controls and $\epsilon_t$ is a zero-mean but heteroscedastic error term. Let $G_t$ be the growth rate of the firm over the past $\delta$ years. Equation (2) can alternatively be written as

\[ G_t = \alpha + (\beta - 1)\ln S_{t-\delta} + \gamma \ln A_{t-\delta} + \sum_{j=1}^{k} \lambda_j Z_j + \epsilon_j \]  

A negative size effect in firm growth is observed when $\beta < 1$ if we estimate equation (2) while a negative age effect in growth means $\gamma < 1$ regardless of whether we are estimating equation (2) or equation (3). Size is measured by the number of full time employees in both Tables 1 and 2. The results reported in Table 1 are those of the estimation of Gibrat’s equation for alternative lengths of the growth period while suppressing industry effects altogether. Gibrat’s law is rejected at the 5% level of significance in favour of smaller firms growing faster during each of the periods considered. In contrast, age effects in growth are evident only in equations referring to the periods 1983–9, 1989–93, 1989–92, 1989–91 and 1991–3, that is, only for periods of between 2 and 6 years duration. When there is an age effect, it is one of younger firms growing faster. Notice also that the relationship is strongest for the period 1989–93, which, with a log-age coefficient of $-0.11$, is quite close to the figure that Dunne and Hughes (1994) reported for UK firms over a 5 year growth period. The absolute value of the coefficient decreases when we increase the growth period to 6 years. It also falls progressively as we reduce $\delta$ below 4 years until it becomes negligible for a 1 year growth interval. The P-value of the age effect also seems to increase monotonically as we increase or decrease $\delta$ away from four years.

The Ethiopian data therefore seem to be consistent with the predictions of the passive learning model but rule out active or exploratory learning of the Nelson–Winter and Ericsson–Pakes models. However, Table 1 indicates that it would be incorrect to attribute the size effects read in it exclusively to passive learning. The size effects observed for growth periods longer than 6 years are not accompanied by a similar age effect and cannot therefore be due to such learning. They are, on the other hand, consistent with any one of dynamic economies of scale, competitive diffusion and transient differences in productive efficiency. Table 1 also suggests that the length of the phase
of passive learning in the life cycle of firms in manufacturing industries in Ethiopia may not be much longer than 6 years. This might even be a more general result since no previous study has, to our knowledge, reported a negative age effect for growth periods longer than 5 years despite the availability of data for much longer periods. That age effects cannot be detected for growth periods shorter than 2 years in the Ethiopian sample could be because the noise-to-signal ratio is too high when the period of measurement is so short.

Table 2 deals exclusively with a 4 year growth period — 1989–93.
Note, that the P-value of the coefficient of the age variable for the corresponding regression in Table 1 is rather high at ~0.12 when the standard error estimate is corrected for heteroscedasticity. However, age effects are significant at almost any level when we focus on ‘small’ or ‘young’ firms, as we do in Table 2. In order to arrive at a working definition of smallness and youth we experimented with alternative cut-off points. An initial division of the sample into firms employing five workers or less and those employing more than five workers led

<table>
<thead>
<tr>
<th>Variables</th>
<th>All firms</th>
<th>Small firms(^a)</th>
<th>Young firms(^b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>1.416</td>
<td>2.587</td>
<td>1.768</td>
</tr>
<tr>
<td>(0.297)</td>
<td>(0.666)</td>
<td>(0.398)</td>
<td></td>
</tr>
<tr>
<td>Log of employment size in 1989</td>
<td>0.78</td>
<td>0.371</td>
<td>0.706</td>
</tr>
<tr>
<td>(0.069)</td>
<td>(0.172)</td>
<td>(0.76)</td>
<td></td>
</tr>
<tr>
<td>Log of age of establishment in 1989</td>
<td>-0.083</td>
<td>-0.178</td>
<td>-0.158</td>
</tr>
<tr>
<td>(0.07)</td>
<td>(0.085)</td>
<td>(0.079)</td>
<td></td>
</tr>
<tr>
<td>State-owned enterprises</td>
<td>0.811</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.269)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Food and beverages</td>
<td>-0.569</td>
<td>-0.563</td>
<td>-0.565</td>
</tr>
<tr>
<td>(0.165)</td>
<td>(0.634)</td>
<td>(0.317)</td>
<td></td>
</tr>
<tr>
<td>Textiles</td>
<td>-0.793</td>
<td>1.232</td>
<td>-1.17</td>
</tr>
<tr>
<td>(0.206)</td>
<td>(0.622)</td>
<td>(0.34)</td>
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<tr>
<td>Garments</td>
<td>-0.631</td>
<td>-1.081</td>
<td>-0.732</td>
</tr>
<tr>
<td>(0.192)</td>
<td>(0.624)</td>
<td>(0.314)</td>
<td></td>
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<tr>
<td>Leather and leather products</td>
<td>-0.387</td>
<td>-1.037</td>
<td>-0.378</td>
</tr>
<tr>
<td>(0.168)</td>
<td>(0.624)</td>
<td>(0.325)</td>
<td></td>
</tr>
<tr>
<td>Furniture and woodwork</td>
<td>-0.507</td>
<td>-0.774</td>
<td>-0.512</td>
</tr>
<tr>
<td>(0.187)</td>
<td>(0.619)</td>
<td>(0.325)</td>
<td></td>
</tr>
<tr>
<td>Metal work</td>
<td>-0.587</td>
<td>-0.903</td>
<td>-0.656</td>
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<tr>
<td>(0.226)</td>
<td>(0.641)</td>
<td>(0.369)</td>
<td></td>
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<thead>
<tr>
<th>N</th>
<th>159</th>
<th>69</th>
<th>94</th>
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<tbody>
<tr>
<td>R(^2)</td>
<td>0.87</td>
<td>0.20</td>
<td>0.54</td>
</tr>
</tbody>
</table>

Dependent variable = log of employment in 1989 (heteroscedastic-consistent standard errors are given in parentheses).
\(^a\)Firms employing >10 workers in 1989.
\(^b\)Firms aged 15 years or more in 1989.
to a rejection of Gibrat’s law in both groups. We then raised the cut-off point to 10 workers. This time, a size effect was detected for firms employing 10 workers or less, but not in the subsample of larger firms. We experimented in a similar fashion with alternative cut-off points for youth. A negative age effect was present in both subsamples for young firms defined as those aged 5 years or less. The result was the same when the cut-off point was raised to 10 years. However, raising the threshold to 15 years led to the disappearance of the age effect for the subsample of older firms. Hence the definitions of ‘young’ firms as those aged 15 years or less and small firms as those employing 10 workers or less are used in Table 2.

We can see from Table 2 that market selection is not the only source of differences in the growth performance of firms. As expected, we see strong industry effects as well in the sense that the average growth rate of a firm depends on the growth rate of market demand. However, we also find that selection effects are a more important determinant of the growth performance of the average firm than industry effects, as can be seen from Table 3. By the average firm we mean a firm the initial size and initial age of which is equal to the corresponding sample mean. Table 3 shows that, in the absence of selection effects, such a firm would grow fastest in the woodwork and furniture industry. However,

<table>
<thead>
<tr>
<th>Industry</th>
<th>Growth rate</th>
<th>Industry effect</th>
<th>Size effect</th>
<th>Age effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food and beverages</td>
<td>-0.03</td>
<td>0.65</td>
<td>-0.69</td>
<td>0.01</td>
</tr>
<tr>
<td>Textiles</td>
<td>-0.47</td>
<td>0.29</td>
<td>-1.25</td>
<td>0.49</td>
</tr>
<tr>
<td>Garment</td>
<td>-0.03</td>
<td>1.30</td>
<td>-0.36</td>
<td>-0.97</td>
</tr>
<tr>
<td>Leather products</td>
<td>0.28</td>
<td>0.90</td>
<td>0.48</td>
<td>-0.90</td>
</tr>
<tr>
<td>Furniture and woodwork</td>
<td>-0.17</td>
<td>1.73</td>
<td>-1.22</td>
<td>-0.69</td>
</tr>
<tr>
<td>Metal work</td>
<td>-0.05</td>
<td>1.11</td>
<td>-1.22</td>
<td>0.06</td>
</tr>
</tbody>
</table>
age effects are quite strong in this industry, and taking these into account, the firm would grow at 60%. This is assuming the absence of size effects in growth; however, there are such effects in the industry that, taken on their own, would make the firm grow at a rate only 29% of that implied by the growth rate of market demand. The combined effect of age and size effects is consequently that the firm would actually contract by 17% over the 5 year period despite the fact that the growth rate in market demand is positive and large. A reading of the other rows of the table in the same way leads to two conclusions. First, there are significant inter-industry differences in the strength of selection effects. Secondly, the same effects are strong everywhere, ranging from 70 to 260% of industry effects.

2.4 Selection, Productivity and Intra-industry Reallocation

The absence of satisfactory industrial census data has so far excluded the analysis of producer turnover in Sub-Saharan Africa. As a result, we do not yet have evidence of market selection in what we have termed the ‘productivity-turnover’ category. However, we do find that permanent inter-firm differences in productive efficiency are behind the age–size effects in growth that we have detected in the Ethiopian survey data. The evidence is in the form of fixed firm effects in estimated frontier production functions. If smaller firms grow faster and younger firms grow faster as a signal for passive learning, we should have positive age and size effects in productivity. In other words, firm effects in productivity must increase with the current firm age and firm size. This is what we see in Table 4. The regression results reported in the table are based on firm and time periods to which the firm growth equations of Table 2 refer. In the first column of the table we regress the deviation of fixed firm effects from industry sample means on the log of the firms current age, the square of the same, the log the firm’s current employment size and industry dummies. The regressors of the equation estimated in the second column are the same but the dependent variable here is the deviation from the industry sample mean of the Battese–Coeli predictor of technical efficiency. For convenience, we refer to the deviation of the firm fixed effects in technical efficiency from the industry sample mean as ‘Score1’. We refer to the deviation of the Battese–Coeli predictor from the industry sample mean as ‘Score2’. We see in both columns that older firms are more productive per given size while bigger firms are more productive per
given age, which, taken in conjunction with the age–size effects in growth as reported in Table 2, is a strong indication of passive learning as a selection mechanism in Ethiopian industries.

What is the evidence on intra-industry reallocation? If the age–size effects in firm-level productivity and growth we have just described signal a process of market selection in African industries, then the survey data in which the effects are detected should also show a process of reallocation of resources: from less productive firms to more productive ones.

A preliminary analysis of balanced panels of firms from RPED data sets from the Cameroon, Côte d’Ivoire, Ethiopia and Ghana indicates that this is indeed the case (T. Mengistae and A. Zeufack, in progress; reported in Tables 5–7).

The data for Cameroon and Ethiopia were obtained from surveys carried out during 1993–5. Those for Ghana refer to the period 1991–3, while those for Côte d’Ivoire refer to 1994–5. For our purpose, we selected firms on which observations were made in every wave of each survey programme. The number of firms included in this analysis is

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Score1</th>
<th>Score2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-1.7109</td>
<td>-0.6725</td>
</tr>
<tr>
<td></td>
<td>(0.2323)</td>
<td>(0.3723)</td>
</tr>
<tr>
<td>Log of firm age</td>
<td>0.3726</td>
<td>0.5337</td>
</tr>
<tr>
<td></td>
<td>(0.1027)</td>
<td>(0.3390)</td>
</tr>
<tr>
<td>Square of Log of firm age</td>
<td>-0.0895</td>
<td>-0.1604</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.083)</td>
</tr>
<tr>
<td>Log of employment size</td>
<td>0.4315</td>
<td>0.1754</td>
</tr>
<tr>
<td></td>
<td>(0.0394)</td>
<td>(0.0626)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Score1</th>
<th>Score2</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>125</td>
<td>125</td>
</tr>
<tr>
<td>R²</td>
<td>0.47</td>
<td>0.14</td>
</tr>
</tbody>
</table>

Heteroscedasticity-consistent standard errors are given in parentheses. The regression includes industry dummies the coefficient estimates of which are not reported here.
therefore considerably lower than the number of firms covered in each wave of a country survey. The advantage of limiting ourselves to a balanced panel in each case is that we can then think in terms of allocation of resources among a fixed set of firms tracked over time.

We report in column 8 of Table 5 the growth rate of labour productivity (i.e., value added per worker) in the representative firm each country sample. With the exception of the Côte d’Ivoire sample, this rate is positive and substantial, ranging from 10% in Ethiopia over a 3 year period to 45% for the Ghanian sample over the same length of time. However, it is also clear from the other columns of the same table that these rates conceal large disparities in the productivity of firms in each country sample. Thus only 45–63% of firms have actually registered growth in productivity in the three countries where the rate was positive for the representative firm. Similarly, labour productivity actually grew in more than one-third of firms in the Côte d’Ivoire sample, despite the fact that productivity fell by 58% in the representative firm of the same sample.

In Table 6 we report the shares in sample total value added, capital stock and employment of firms in which labour productivity grew.

### Table 5: Weighted average rates of growth in labour productivity in manufacturing firms: Cameroon, Côte d’Ivoire, Ethiopia and Ghana

<table>
<thead>
<tr>
<th>Country</th>
<th>N</th>
<th>%</th>
<th>N</th>
<th>%</th>
<th>N</th>
<th>%</th>
<th>All firms</th>
<th>More prod.</th>
<th>Less prod.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cameroon</td>
<td>102</td>
<td>100</td>
<td>52</td>
<td>51.0</td>
<td>50</td>
<td>49.0</td>
<td>0.42</td>
<td>0.57</td>
<td>–0.61</td>
</tr>
<tr>
<td>Côte d’Ivoire</td>
<td>103</td>
<td>100</td>
<td>41</td>
<td>40.0</td>
<td>62</td>
<td>60.0</td>
<td>–0.58</td>
<td>0.34</td>
<td>–0.91</td>
</tr>
<tr>
<td>Ethiopia</td>
<td>154</td>
<td>100</td>
<td>64</td>
<td>44.1</td>
<td>81</td>
<td>55.9</td>
<td>0.10</td>
<td>0.71</td>
<td>–0.45</td>
</tr>
<tr>
<td>Ghana</td>
<td>131</td>
<td>100</td>
<td>83</td>
<td>63.4</td>
<td>48</td>
<td>36.6</td>
<td>0.45</td>
<td>0.81</td>
<td>–0.34</td>
</tr>
</tbody>
</table>

aFirms in which labour productivity grew.
bFirms in which labour productivity fell.
during the first wave of each country survey and during the last wave of the same survey. We see from the table that, in each case, firms for which labour productivity grew increased their output and capital stock both in absolute terms and as a percentage share of the sample total. However, firms with growing labour productivity also registered reduction in employment in absolute terms as well as a percentage share of the sample total. In Ghana, for example, firms in which productivity grew increased their share of value added from 56.6% in 1991 to 77.2% in 1993. The share of the same firms in the sample total capital stock also increased, from 61.1 to 82.2%, during the same period, while their share in sample total employment dropped from 77.1 to 73.6%.

The decline in the employment shares along with a rise in capital stock shares of firms in which labour productivity grew means that the growth in labour productivity in the same firms could be entirely due to growth in their capital–labour ratio relative to the other firms. In other words, what we are observing could be higher investment in capital stock leading to higher labour productivity, rather than the other way round. In order to distinguish between the opposing directions of causality, we run a least squares regression of the growth rate of capital stock on the beginning-of-period value added per worker and beginning-of-period capital stock per worker, the results of which are reported in Table 7. We see from the table the expected result— that the rate of investment is lower for firms in which the capital–labour ratio is higher and, hence, the expected marginal productivity of capital is higher. However, it is also clear that, controlling for initial

<table>
<thead>
<tr>
<th>Country</th>
<th>Initial</th>
<th>Terminal</th>
<th>Initial</th>
<th>Terminal</th>
<th>Initial</th>
<th>Terminal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cameroon</td>
<td>81.8</td>
<td>93.1</td>
<td>71.1</td>
<td>89.3</td>
<td>81.2</td>
<td>74.5</td>
</tr>
<tr>
<td>Côte d’Ivoire</td>
<td>18.0</td>
<td>36.0</td>
<td>44.0</td>
<td>48.0</td>
<td>34.0</td>
<td>26.0</td>
</tr>
<tr>
<td>Ethiopia</td>
<td>32.8</td>
<td>55.8</td>
<td>43.6</td>
<td>71.1</td>
<td>64.3</td>
<td>60.4</td>
</tr>
<tr>
<td>Ghana</td>
<td>56.6</td>
<td>77.2</td>
<td>61.1</td>
<td>82.2</td>
<td>77.1</td>
<td>73.6</td>
</tr>
</tbody>
</table>
capital intensity, investment is greater the higher the initial labour productivity. There is therefore good reason to believe that at least some of the redistribution of capital stock and output reported in Table 6 represents reallocation of resources to more efficient producers.

3. Investment

As we noted in the previous section, the literature on firm dynamics is in principle concerned with the same question as studies of firm investment. However, in practice, the focus has been rather different. As we have seen, empirical work on firm dynamics has focused on firm age and size effects as evidence of various market selection processes. By contrast, empirical work on investment has invariably controlled for age and size effects but has focused on the possible effects of financial repression on investment.

Donors commonly and understandably believe that investment is constrained by firms’ access to finance. The growth regressions literature gives some support for the thesis that finance is important for growth (e.g., King and Levine, 1993) but Africa’s lack of financial depth seems to explain only a very small part of its poor growth performance (Collier and Gunning, 1999). Micro-studies of the effect of finance on investment investigate the relationship between firm-level profitability and investment. If the firm had access to a perfect
capital market its investment decision would be driven by the given (and common) interest rate. Hence the firm’s investment rate would be independent of its profitability. However, there is considerable evidence of a positive relationship between profits and investment, both for developed countries (e.g., Bond and Meghir, 1994)\(^2\) and for developing countries (for Indonesia see, e.g., Harris et al., 1994). Under capital market imperfections, in particular if access to external finance is rationed, capital costs become firm specific and a firm’s profitability affects its capacity to finance investment.

Bigsten et al. (1999a) investigated the relationship between profitability and investment for four African countries — Cameroon, Ghana, Kenya and Zimbabwe — using the RPED surveys. For the 739 firms in their data set the median investment rate \((I/K)\) is only 0.004;\(^3\) however, these firms are highly profitable: the profit rate (profits as a percentage of the value of the capital stock) is 38. Hence it appears that African manufacturing firms have extremely low investment rates but atypically high profit rates. This is supported by production function estimates that suggest a rate of return on physical capital of 22\% (Bigsten et al., 2000). Whether this result generalizes to other countries is not clear; this is an important area for future research.

Most papers on the determinants of investment assume that firms maximise profits, with a valuation function of the form:

\[
W_t(K_t) = \max \{ \Pi(K_t, L_t, I_t) + \beta_t E[W_{t+1}(K_{t})] \}
\]

where \(\Pi(.)\) is the net revenue function, \(K_t\) is the capital stock, \(L_t\) is labour and \(I_t\) is investment. Expectations conditional on information available at time \(t\) are denoted by \(E[t].\) Two types of estimating equations (both derived from this general valuation function) have been used in the literature:

\[
(I/K)_{t} = \alpha_{0} + \alpha_{1}(I/K)_{t-1} - \alpha_{2}(I/K)_{t-1}^{2} - \alpha_{3}(C/K)_{t-1} + \alpha_{4}(V/K)_{t-1} + \alpha_{5}(B/K)_{t-1}^{2} + d_{t} + \eta_{t} + v_{it}
\]

with \(d_{t}\) a time dummy, \(\eta_{t}\) an unobserved firm-specific effect and \(v_{it}\) the error term. \(C\) denotes profits (measured as value added minus the

\(^2\) This is similar to the situation in labour economics, where empirical papers typically report evidence of labour market inefficiencies (such as rent sharing), even for developed countries such as the USA.

\(^3\) The average rate is 12\% but, since the distribution of investment rates is highly skewed, we prefer to use the median.
wage bill, $V$ value added and $B$ outstanding debt. Equation (4) is a flexible accelerator formulation with growth in value added as a proxy for growth in demand. Equation (5) is an Euler specification.

A logit for the decision to invest shows that age and size effects are important: larger firms are more likely to invest, older firms less likely. However, estimating equation (8) to investigate the determinants of the rate of investment Bigsten et al. find no age and size effects. Apparently age and size effects matter for the decision to invest but not for the amount invested. They do find a significant effect of the profits rate ($C/K$). Using fixed effects, they use three different specifications to test for the robustness of this profit term. The first is the flexible accelerator specification of equation (8), the second is the Euler specification of equation (9), while the third is a general formulation in which the flexible accelerator term (the growth in value added) is added to the Euler specification. The first of these estimates is reproduced in Table 8. Note that the profit effect is significant for small firms but not for large firms (defined as those with $>100$ employees). This is also true in the other two specifications.

The most striking finding is the size of the profit effect. In the accelerator specification the coefficient on the profit term is 0.06, both for small firms and for all firms. In the Euler specification this rises to 0.07 and in the general specification to 0.10 (again, both for small firms and for the pooled sample). The evidence for Ethiopia suggests even lower coefficients (J.W. Gunning, T. Mengistae and P. Collier, in progress). A flexible accelerator equation, using the data on the 151 private firms covered by the 1993 and 1995 waves of the Ethiopian Industrial Enterprise Survey, gives a significant effect of profits on investment. However, the estimated coefficient is only 0.00057.

This evidence is difficult to reconcile with the thesis that firm investment rates are low because of rationed access to external finance. While there is evidence of imperfect access, particularly for small firms (for Zimbabwe see, e.g., Fafchamps and Oostendorp, 1999), the evidence for Cameroon, Ghana, Kenya and Zimbabwe indicates that this is an unsatisfactory explanation for low investment rates. If investment were liquidity constrained, then changes in profits would have a powerful effect on investment whereas the fixed effect estimates suggest that, of an additional unit of profits, only 6–10% is used to raise the rate of investment.

If financial constraints cannot explain the low investment rates, then what can? Bigsten et al. (1999a) suggest that investment is low because
of the risk faced by firms. This is consistent with the macroeconomic literature on the effect of risk on investment and the fact that all four countries were characterised by macroeconomic instability in the survey period of the early 1990s. Kenya, Ghana and Zimbabwe experienced high and variable inflation and large exchange rate adjustments while Cameroon faced substantial uncertainty about the sustainability of the fixed CFA franc exchange rate.

Risk matters because most investments are difficult to reverse — a point stressed in Serven (1997). As stressed by Dixit (1989) and by Dixit

<table>
<thead>
<tr>
<th></th>
<th>All Firms[1]</th>
<th>Large Firms[2]</th>
<th>Small Firms[3]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.05</td>
<td>-0.04</td>
<td>-0.07</td>
</tr>
<tr>
<td></td>
<td>[1.3]</td>
<td>[0.8]</td>
<td>[1.0]</td>
</tr>
<tr>
<td>Value-added/Capital(t-1)</td>
<td>0.01</td>
<td>-0.003</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>[1.6]</td>
<td>[0.4]</td>
<td>[1.9]</td>
</tr>
<tr>
<td>Profit</td>
<td>0.06</td>
<td>0.04</td>
<td>0.06</td>
</tr>
<tr>
<td>Rate(t-1)</td>
<td>[3.5]**</td>
<td>[0.6]</td>
<td>[4.0]**</td>
</tr>
<tr>
<td>Ln(size)(t-1)</td>
<td>0.04</td>
<td>-0.02</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>[0.3]</td>
<td>[0.1]</td>
<td>[0.2]</td>
</tr>
<tr>
<td>Borrowing/Capital(t-1)</td>
<td>0.34</td>
<td>0.24</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>[1.7]</td>
<td>[0.7]</td>
<td>[1.2]</td>
</tr>
<tr>
<td>Borrowing/Capital^2(t-1)</td>
<td>-0.14</td>
<td>-0.09</td>
<td>-0.13</td>
</tr>
<tr>
<td></td>
<td>[1.8]</td>
<td>[0.5]</td>
<td>[1.6]</td>
</tr>
<tr>
<td>Ghana</td>
<td>0.07</td>
<td>-0.27</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>[0.8]</td>
<td>[1.0]</td>
<td>[1.1]</td>
</tr>
<tr>
<td>Kenya</td>
<td>0.04</td>
<td>-0.05</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td>[0.6]</td>
<td>[0.7]</td>
<td>[0.7]</td>
</tr>
<tr>
<td>Cameroon</td>
<td>0.09</td>
<td>0.10</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>[0.9]</td>
<td>[0.6]</td>
<td>[0.8]</td>
</tr>
<tr>
<td>N</td>
<td>223</td>
<td>73</td>
<td>150</td>
</tr>
<tr>
<td>Adj. R^2</td>
<td>0.18</td>
<td>-0.02</td>
<td>0.21</td>
</tr>
</tbody>
</table>

All variables except country dummies are differenced. The dependent variable is \(\Delta I/K(t-1)\). Source: Bigsten et al. (1999a). The figures in brackets are the robust one-step t-statistics reported in the DPD programme (Arellano and Bond, 1988).

*Significant at the 5% level
**Significant at the 1% level.
and Pindyck (1994), in the presence of irreversibilities, the potential investor has an incentive to remain liquid until risk is resolved. The value of waiting is that that the investor avoids a costly mistake. By remaining liquid he foregoes the higher return which he might have realised if he had invested immediately, before the risk was resolved. However, this may well be more than offset by the very high costs he would incur (because of the irreversibility of investment) if he chose to invest and then found the rate of return to be low.

Irreversibility is clearly an extreme case. The more general case, where reversing investment is feasible but costly, has been analysed by, for example, Abel and Eberly (1994; cf. Serven, 1997, pp. 236–7). In this framework there is a ‘two-trigger’ investment policy. When Tobin’s $q$ exceeds some bound, investment is positive, while below some lower threshold, optimal investment is negative. In between there is a zone of inactivity: as long as $q$ is between the two critical values the firm will choose not to adjust its capital stock. In these models the effect of risk is ambiguous: risk raises the threshold above which $q$ must rise if investment is to take place, thus increasing the zone of inactivity. However, the effect on the return to capital may work the other way. For example, if the marginal productivity of capital is convex in a variable subject to risk (say the price of the firm’s output), then (by Jensen’s inequality) a mean preserving spread will raise the expected value of the marginal product. However, the (aggregate) evidence seems to support a negative effect (Serven, 1997, pp. 244–5): uncertainty reduces the rate of investment.

This has important policy implications. As Serven points out: ‘the predictability of the incentive framework — relative prices, demand, interest rates, taxes — may be much more important than the level of the incentives themselves’. Since adjustment programmes tend to focus on the latter (the level of the incentives), this has important policy implications. Indeed, structural adjustment may make matters worse by increasing the risk of policy changes.4

4 The literature on the effect of structural adjustment has focused on the issue of the credibility of adjustment policies. However, adjustment will affect investment even if fully credible. This may be because the trade policy favoured a capital-intensive sector so that liberalisation lowers the economy’s optimal capital stock. Alternatively, trade policy often involves lower tariff rates for capital goods than for intermediate inputs or consumer goods. In that case, liberalisation amounts to the removal of an implicit capital subsidy, which will lower investment irrespective of the factor intensities of the protected and unprotected sectors (see Buffie, 1992; Collier and Gunning, 1992, 1996).
While there exists a considerable theoretical literature on the effect on investment of the conjunction of risk and irreversibility, there is as yet very little empirical evidence. In the time series literature there have been some attempts. For example, Fielding (1993) constructs a measure of the variability of capital goods prices and finds (p. 321) that on average the investment rate in Kenya was only 86% of what it would have been in the absence of uncertainty (thus proxied). Kumsar and Mlambo (1995) consider the evidence for forty African countries for the period 1970–1993. They use three measures of macroeconomic instability: the inflation rate, the terms of trade volatility and the variability of the fiscal deficit. From 1980 onwards all three measures have a negative and significant effect on investment.

For Africa there is little microeconomic evidence on the effects of risk. The two-threshold model has not yet been estimated directly. A very interesting attempt to test the importance of risk and irreversibility is that of Pattillo (1999). She uses the RPED Ghana data to test the hypothesis that differences between firms in investment rates can be explained partly in terms of differences in reversibility and in the firms’ perception of uncertainty. The RPED survey collected some information on the use of second-hand capital goods and on whether firms sold, bought or leased capital equipment. Pattillo classified firms which reported having leased capital goods, bought used equipment, or sold capital goods as firms for which investment is relatively easy to reverse. Uncertainty was measured by the standard deviation (across firms in a given sector) of expected changes in demand (data were collected on one- and three-year ahead expectations of demand). Pattillo shows that the effect of uncertainty (thus measured) on the rate of investment is negative. She also shows that this negative effect is considerably stronger for firms facing relatively irreversible investment decisions.

An important point to note is that African economies may be atypical in the degree of irreversibility. Partly as a result of past trade policies, the industry structure in manufacturing tends to be highly monopolistic. An implication is that a market for second-hand sector-specific equipment is inevitably very thin: in the absence of competitors, equipment can only be sold at deep discounts.

Fafchamps et al. (2000) have used the Zimbabwe RPED data to investigate firms’ responses to risk. They show that those firms which are most exposed to risk (e.g., those which have an unreliable supply
of inputs) respond by holding large stocks of inventory and cash, presumably at the expense of fixed investment.

A problem with much of the literature on the effect of risk on investment is the crudeness of the risk measures used. This is not inevitable but simply reflects the fact that existing survey instruments were not designed to measure the risks faced by firms. A commonly used measure is the standard deviation, but this measures volatility rather than risk. Where policy credibility is one of the most important sources of risk this may be serious. For example, under a fixed exchange rate regime the government’s intention to maintain the current rate may be incredible. However, the risk of exchange rate adjustment that firms perceive will obviously not be picked up by the standard deviation of the exchange rate (which may well have been stable for an extended period).

The RPED surveys contained questions about expectations, both for macroeconomic variables (inflation, interest rates, the exchange rate) and firm-specific variables (employment, output).

Respondents were asked to provide point estimates and there is no measure of the degree of confidence with which these expectations are held. Clearly, if firms report wildly different expectations, this is likely to reflect risk (although not necessarily so: firms can have idiosyncratic expectations which differ substantially between firms while being held with great confidence by each). This is the justification for Pattillo’s use of standard deviation of expectations of firms in the same sector as a measure of risk. She finds considerable dispersion of expectations for Ghana. For Zimbabwe (Figure 1) the dispersion of expectations is also widely spread, particularly in the case of exchange rate expectations, suggesting considerable uncertainty. This is reinforced by the large number of respondents (almost half of the sample) answering ‘don’t know’ to the question about expectations.

A key question concerns the effect of expectations on investment. Bigsten et al. (1998) used the RPED data to estimate an investment equation incorporating firm-specific expectations. They found strong effects. For example, for Zimbabwe they found that if firms expected on average an additional depreciation of 10%, this would raise the level of investment by 7.7%. Similarly, a 10% increase in the expected interest rate would reduce the mean investment rate by almost 20%. The effect of expectations on investment has also been tested on the Ethiopian survey data (J.W. Gunning, T. Mengistae and P. Collier, in progress). When three expectational variables (for the growth of the
firm’s sales, the bank lending rate and the exchange rate) are included in an accelerator-type investment equation only exchange rate expectations turn out to be significant.

Panel data can also be used to explore the dynamic pattern of investment. Bigsten et al. (1999b) show that the typical pattern is not the one implied by the standard model of convex and symmetrical (e.g., quadratic) adjustment costs — that model implies continuous, small adjustments in the capital stock. In fact, the firm-level evidence shows periods of zero investment, occasionally interrupted by lumpy investments. Rather surprisingly, the evidence on fixed costs (lumpiness in investment) is not strong. However, the evidence does support the importance of irreversibilities.
4. Conclusion

In the ongoing effort to explain Africa’s poor growth record, some observers point the finger at the low investment rate that has characterised most economies of the region. Others contend that there is no link between the rate of investment and GDP growth in Africa, and argue that both low growth and low investment rates are a consequence of the low productivity of capital stock, which the ‘insulation of producers from market forces’ has generated. Both views are based on cross-country growth regression results. In this paper we have attempted to piece together the microeconomic evidence on the determination of the rate and productivity of investment in manufacturing activities.

The available micro-evidence does not seem to support the view that the return to investment in Africa is too low. Not only does it suggest that profitability is high in manufacturing firms, but industry level average productivity of investment also appears to have improved significantly in the 1990s as a result of a process of market selection. There is no evidence that markets in Africa are any more tolerant of inefficient producers or poor investment than they are elsewhere. The evidence for selection has come in two forms. The first is that the same signals of selection in firm growth that studies have reported in developed economies are also evident in African data sets. That is, as is often the picture elsewhere, smaller firms grow faster per given age and younger firms grow faster per given size. According to the theories of market selection, this is possible only because resources are being continually reallocated from less efficient to more efficient firms through producer turnover and differential growth rates arising from inter-firm differences in productive efficiency. Secondly, and more directly, investment rates are higher for firms which have had a history of higher productivity.

However, the apparently high potential returns to investment have not induced high investment rates. Indeed, the median rate of investment for a sample of firms pooled across four countries is almost zero. The work on the determinants of investment that we have reviewed indicates that the financial constraints faced by firms do not explain the very low rates of investment. The most likely reason is that firms require high rates of return because of the risks they face. More direct evidence on this point is needed if only because of its policy implications. Adjustment programmes have tended to focus on the (mean)
incentives faced by firms rather than on their predictability. Where surveys provide evidence on expectations, exchange rate expectations seem important for investment decisions. Expectations are diverse, but there is at present no evidence that this adversely affects investment.

We hasten to add that in Sections 2 and 3 we have relied heavily on a small set of surveys. For many African countries survey data suitable for analysing the determinants of investment and its productivity do not yet exist. Extending the set of surveys is, in our view, a high priority. For example, a key finding in Section 3 is that manufacturing firms invest very little and that this cannot be explained as the result of the lack of external finance. However, this finding is based on surveys for only five countries. A key research priority is to investigate to what extent these results generalise. New surveys should not simply replicate but should focus on the areas where current surveys are very weak: expectations and adjustment costs. Expectations data have been collected in a continuous form for only a few countries (Uganda, Ethiopia, Kenya and Zimbabwe), and none of the surveys have attempted to obtain direct measures of credibility.

Similarly, at present researchers must infer the shape of the adjustment cost function from observed investment behaviour. There has been no attempt yet to measure this function more directly. For example, surveys have not collected information on fixed costs involved in investing and very little on the reversibility of investment.

It would be important to get direct measures of the firms’ perceptions of the risks they perceive. At present risk is identified as a key determinant of investment behaviour, but this is largely based on indirect evidence.

The gap in microeconomic evidence is even more glaring when it comes to producer turnovers. Producer entries and exits are a major source of industry level variation in productivity and the efficiency of investment. Unfortunately no sample survey can capture them however carefully it is designed. The gap here can only be bridged by industrial censuses.

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Determinants of African Manufacturing Investment 79

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