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Adjustment Costs, Irreversibility and Investment Patterns in African Manufacturing

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Abstract

This paper examines dynamic patterns of investment in Cameroon, Ghana, Kenya, Zambia and Zimbabwe, assessing the consistency of those patterns with different adjustment cost structures. Using survey data on manufactured firms, we document the importance of zero investment episodes and lumpy investment. The proportion of firms experiencing large investment spikes is significant in explaining aggregate manufacturing investment. Taken together, evidence from descriptive statistics, average investment regressions modeling the response to capital imbalance, and transition data analysis indicate that irreversibility is an important factor considered by firms when making investment plans. The picture is not unanimous however, and some explanations for the mixed results are proposed.

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Contents

I. Introduction

This paper seeks to determine whether firm level investment behavior in the manufacturing sectors of Cameroon, Ghana, Kenya, Zambia and Zimbabwe is more accurately described by standard theory based on quadratic adjustment costs or by alternative models, based on irreversibilities or fixed costs. The importance of this issue stems first from a theoretical perspective, given that the adjustment cost function constitutes one of the cornerstones of the investment equation, and misspecification of adjustment costs is likely to yield a misspecified investment model. Second, empirically, information on the structure and size of adjustment costs is important for understanding how investment responds to changes in fundamentals. For example, some non-quadratic adjustment cost models imply that firm investment is nonlinear: periods of little response to shocks can be followed by intensive responses to both current and accumulated shocks. The structure of adjustment costs also has significant implications for understanding aggregate investment dynamics.[2]

Theoretical models in the literature, some recent, stress that one of the implications of fixed costs or irreversibilities is that it periodically will be optimal for the firm to refrain from investing altogether.[3] Under fixed costs there are increasing returns in the adjustment cost function, and firms therefore wait and invest infrequently, in large lumps, in order to avoid paying the fixed costs during many periods. Similarly, irreversibilities or kinked adjustment cost functions imply a discontinuity in the marginal cost to investment, which creates an inaction range within which fluctuations in marginal returns are insufficient for investment to respond. In contrast, in the standard quadratic framework the adjustment cost function is zero at zero investment, and continuously differentiable with marginal costs increasing in the size of the investment. This implies that the firm responds to shocks by spreading a given investment over a longer period, i.e. making continuous small adjustments every period. There is no reason, in this framework, for zero investment episodes.

The fact that sub-Saharan Africa (SSA) has lower investment levels than other regions makes it an interesting place to explore adjustment costs. This paper uses firm level

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[2]If adjustment costs are quadratic, aggregation of microeconomic investment policies is straightforward, yielding investment dynamics linear in the underlying shocks or fundamentals. Whenever irreversibilities or fixed adjustment costs are significant this is no longer the case, however, and it becomes important to track the fraction of firms that are undertaking large bursts of investment activity, or investment spikes. See Doms and Dunne (1997), Cooper, Haltiwanger and Power (1997), Nilsen and Schianterelli, (1998) and Gelos and Isgut (1999) for empirical investigations of the relationship between the fraction of firms undergoing a primary investment spike and variations in aggregate manufacturing investment.

[3]Irreversibilities have been modeled by either constraining investment to be non-negative (because there are infinite disinvestment costs) or including proportional (linear) adjustment costs, but making disinvestment costly (as in models of piecewise linear adjustment costs where the sale price of capital is lower than the purchase price).

panel data from the five countries mentioned above spanning the first part of the 1990s, and in this sample investment often occurs in lumps, and is otherwise zero. Since the binary decision of whether or not to invest is at the center of models based on fixed costs or irreversibilities, the significant representation of firms "doing nothing" in the data set makes it a useful sample for analyzing adjustment costs. Further, it seems reasonable to anticipate that fixed costs or irreversibilities are more important for manufacturing firms in Africa than in industrialized countries. In SSA firms operate in an environment with shallow and limited secondary markets for capital goods, poor infrastructure, underdeveloped and often badly-functioning financial markets, and the historical legacy of control regimes where many manufacturing activities required licences or permits. Thus there are potentially high information and transaction costs associated with investment, and such costs are more plausibly characterized by fixed components or irreversibilities than by quadratic costs (Rothschild, 1971).

Empirical work on capital adjustment costs is lagging far behind theoretical advances, and to our knowledge this is the first paper based on African data. For other regions, however, there are some recent papers, and we discuss these in detail below. In summary, these studies have used descriptive statistics to document the significance of zero or modest investment episodes and lumpy investment in the United States, Norway, and Colombia and Mexico. While the descriptive analyses seem decisively at odds with quadratic adjustment costs, the econometric evaluation of the microeconomic predictions from two specific adjustment cost models (Caballero and Engel, 1994, and Cooper, Haltiwanger and Power, 1997) has been less clear-cut. When tested, the econometric evidence seems consistent with models of irreversibilities, and only partially, if at all, supportive of fixed adjustment cost models.

Building on this recent empirical literature, our analysis consists of four empirical exercises. First, we use descriptive statistics to analyze the patterns of zero investment and the extent to which investment activity is concentrated in intermittent periods of large expenditures for the firms in our sample. Second, at the country level, we analyze the relationship between the frequency of firms undergoing investment spikes and aggregate manufacturing investment (proxied by the total investment of firms in our country sample), in order to demonstrate the potential aggregate significance of accounting for lumpy investment. In the third and fourth step, we explore capital adjustment patterns along two dimensions: following Caballero and Engel (1994), we analyze how firms respond to contemporaneous imbalances in the capital stock; drawing on Cooper, Haltiwanger and Power (1997), we estimate transition data models to explain dynamic investment behavior. We argue that it is necessary to explore both dimensions in order to distinguish between quadratic costs, irreversibilities, and fixed costs.

The paper is organized as follows: Section 2 discusses theoretical models of non-convex adjustment costs and reviews existing empirical studies; Section 3 presents descriptive statistics and analyses the relationship between investment spikes and aggregate investment; Section 4 discusses the econometrics of transition data models and outlines our empirical approaches; Section 5 presents results from the transition data models; and Section 6 concludes.

II. Theory of Adjustment Costs

It is widely observed that firms do not immediately adjust their capital stocks in response to shocks to the fundamentals. One explanation is that firms incur costs of adjustment when they vary their capital stocks.[4] These costs may stem from several sources: searching for and deciding upon the adequate piece of equipment to be purchased, scrapping the obsolete machines, installing the new capital stock, reorganizing and training the workforce, etc. The largest share of adjustment costs is likely to consist of opportunity costs of foregone output during the period of adjustment (Hamermesh and Pfann, 1996).

Firms operating in developing countries are likely to be faced by a different cost structure than firms in industrialized countries. For our sample of African manufacturing firms, we anticipate four elements of adjustment costs to be particularly important. Firstly, search and decision costs are high because the desired capital goods are often highly firm-specific and/or local markets for capital goods are shallow. It is also clear that SSA's poor roads, communications and ports imply higher costs of searching for the appropriate equipment. Many firms used imported equipment and these costs may be particularly important in this case. Secondly, while investment licences or import permits are no longer required in most of the countries in our sample, we use retrospective data on investment that often extends back to the periods where they were required. There are explicit and implicit costs of obtaining these licences and permits that are independent of the size of the investment. In some countries obtaining tax concessions for equipment purchase is a bureaucratic ordeal, adding another adjustment cost. Thirdly, organizing financing brings about costs that are most evident for external financing, but also present for internal financing in small firms. These costs are to a certain extent determined by how well the financial markets function, and in particular they will be higher where lenders have limited capacity to assess credit risks and rely on other criteria. There are costs to firm's involvement in networks, one benefit of which can be improved access to bank and supplier credit.[5] Fourthly, there are costs of installation and production disruption, for instance due to reorganization or temporary closure of production lines, or due to workers not mastering the new equipment initially. Training, an important source of adjustment costs, will be important for the firms in our sample if training occurs as a part of production. Again, these costs are likely to be important in the poor infrastructure environments of these countries, where water, electricity and transport are often unreliable.

How are costs of the types discussed above affected by the size of the investment? Until very recently, the vast majority of investment models assumed that adjustment costs

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[4]Adjustment costs are costs associated with the sale, purchase or productive implementation of capital goods over and above the price of the goods.

[5]For Kenya and Zimbabwe, Fafchamps (1999) show that ethnicity and networks affect access to supplier credit.

were convex, usually quadratic in the investment magnitude. Quadratic adjustment costs imply that large and rapid changes are extremely costly, so that firms respond to positive shocks by making continuous, small investments. It has long been recognized, however, that the appeal of quadratic adjustment costs comes from the fact that they deliver a linear investment function, and produce smooth linear aggregate dynamics, not that they are a realistic microeconomic assumption.

There are two main types of criticism of quadratic adjustment costs. First, casual empiricism seems to indicate that firms do not continually make small adjustments to their capital stock every time demand conditions and productivity changes. Second, many examples of adjustment costs seem more likely to have a large fixed or decreasing cost component. For instance, the reorganization of production and retraining probably have large indivisibilities and therefore diminishing costs over some range. These processes also use information as an input, which is known to lead to decreasing costs (once a firm has figured out how to reorganize one production line, doing the second one is cheaper). There could also be substantial fixed costs associated with stopping a production line. Indeed, for many of the adjustment cost types discussed above as relevant in SSA there appear to be considerable fixed components, in the sense that costs are, by and large, independent of whether the firm purchases one or ten new machines.

The problem, then, is how to explain our observations of firm behavior: firms often do not adjust to exogenous shocks, but wait and make infrequent, sometimes large adjustments. Models that explain intermittent (but not lumpy) investment have a longer history in the investment literature. Inaction (no investment) can be optimal in irreversible investment models, where investment is constrained to be non-negative because there are infinite disinvestment costs. More generally, inaction is optimal when adjustment costs are linear, but it is costly to undo the adjustment, and exogenous variables can return to their original values after a shock. This would apply to models where the sale price of capital goods is lower than the purchase price, leading to partial irreversibility.[6] In these models, adjustment costs are piecewise linear, with a kink at zero.[7] It is important to note that with kinked costs, or irreversible investment, when the firm does find it optimal to invest, its per period investment will generally be "small", operating to increase or decrease the capital stock in small but rapid bursts.

[6]The first model of irreversible investment was Arrow (1968); see Dixit and Pindyck (1994) for a comprehensive presentation. Abel and Eberly (1994), (1996) and Abel, Dixit, Eberly and Pindyck (1996) model the effective partial irreversibility resulting from a wedge between the purchase and sale price of capital.

[7]Piecewise linearity is not necessary to yield zero investment over some range. In general, a kink at zero is sufficient. Thus, alternative forms, e.g. piecewise quadratic (with a kink at zero), will also result in an inaction range.

In addition, it is quite evident that inaction can also be optimal when the adjustment costs have a fixed, or lump-sum component. The firm will wait until the benefits of adjusting exceed the fixed cost, and in most cases it would not make sense to incur the fixed cost every period. In related literature, there has been extensive development of (S, s) models, which explain adjustment that is both intermittent and lumpy, because the adjustment costs have fixed cost component. Although they have not been specifically applied to a firm investment model, a standard two-sided (S, s) model would imply that most of the time, the firm allows its marginal product of capital (MPK) to fluctuate in response to exogenous shocks and does not invest. Only when the MPK reaches a trigger would the firm invest in a "lump" in order to bring the MPK to a certain return point.

It is clear that the three adjustment cost structures we have discussed—symmetric quadratic, structures with a kink at zero, and increasing returns in the adjustment cost function (because of fixed costs, for example)[8]—will yield considerably different patterns of capital adjustment. Adjustment costs kinked at zero are consistent with zero investment episodes, but not lumpy investment, fixed costs can yield both zeros and lumps, and symmetric quadratic costs imply no zeros or lumps. We turn now to two particular models of adjustment costs, and their empirical predictions.

A. Models of Intermittent and Lumpy Investment

Caballero and Engel (1994) (henceforth CE) modify an (S,s) type of model by assuming that for a given firm, the extent of loss due to adjustment costs can vary over time, as firms face better or worse matches for old machines or production reorganizations of differing degrees of difficulty.[9] Adjustment costs, proportional to foregone profits during reorganization, also differ across firms. When considering an investment decision at a given point, as in a search model, a firm decides whether to "accept" the current adjustment cost, or postpone adjustment and see what the realization of adjustment costs are next period. The model implies that the size of investment varies both across firms and over time for the same firm. As the size of capital stock disequilibrium increases, the firm will be more hesitant to wait for another adjustment cost "draw", and therefore more likely to invest. Instead of fixed (S,s) bands, the optimal adjustment policies of firms are probabilistic. CE show how, in this framework, average investment is an increasing, nonlinear function of the difference between the stock of capital that would be desired if frictions were temporarily removed and the actual capital stock, termed mandated investment.[10]

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[8]For structures with kinks at zero, we will refer to infinite disinvestment costs or piecewise linear costs since these have been focussed on in the literature.

[9]The CE generalization addresses two notable weaknesses of the standard (S, s) model, where (i) whenever a firm decides to invest, its investments would all be of the same size; (ii) adjustment rules are deterministic: with probability one a firm does nothing while it is in the zone of inaction, and then it adjusts with probability one when the MPK hits the trigger.

[10]For the firm's maximization problem to be well-defined in this model, it is crucial that the (continued...)

The basic microeconomic prediction of the CE model is that the probability and size of investment is an increasing, nonlinear function of mandated investment, i.e. the difference between the desired and actual capital stock. The exact shape of this relationship depends on the distribution of fixed adjustment costs. The model's adjustment cost function also includes a degree of irreversibility arising from the higher cost of disinvestment relative to investment. When mandated investment is negative or low, therefore, average investment is predicted to be relatively flat and unresponsive. That is, even though desired capital is less than actual capital, the costliness of disinvestment deters the firm from disinvesting. The average investment function is predicted to be non-linear: on average firms with relatively large shortages of capital relative to desired adjust proportionally more than firms with small shortages; equivalently, firms with large capital excesses disinvest proportionally more than firms with small excesses.

A second framework with fixed costs is the Cooper, Haltiwanger and Power (1997) (CHP) modeling of the firm's decision to replace an indivisible machine. There are two types of adjustment costs in their set-up, a fixed component that is independent of the firm's size, and another component proportional to the firm's output, which represents the loss of output when the new machine is installed and reorganization and retraining reduces productivity. The producer has the choice of replacing an old machine with the leading edge technology: a machine that is more productive. If the producer chooses not to replace the machine, it depreciates at a fixed rate.[11]

CHP show that the solution to their dynamic programming problem can be characterized by a hazard function, which is the rate at which machines are replaced conditional on the time since previous replacement and the aggregate productivity state.[12] In particular, CHP show that the hazard function exhibits positive duration dependence, i.e. that the hazard of replacement is increasing in the time since previous replacement[13] Where does this result come from? The producer makes an investment when the current period fixed costs

[10](...continued)
value function is concave in capital (otherwise optimal investment will be infinite whenever the firm invests). Concavity is accomplished by assuming either decreasing returns to scale in production or that the demand curve for the firm's products is downward sloping.

[11]Although the decision is termed a replacement problem, it can be interpreted as relevant to expansion investment since the producer can choose a more productive machine.

[12]Thus, in duration data terminology, the "risk set" consists of firms that have not yet invested, and the "failure", is investment at a given point in time.

[13]The model focuses on investment in machine replacement, which the authors interpret as the decision to make a large, lumpy investment. They examine the slope of the hazard for large investment episodes, or investment spikes. In Section 5 we estimate hazards for both investment spikes and all positive investment episodes.

are smaller than the future benefits. The benefits are a more productive and less depreciated capital stock. However, in periods soon after an investment has been made, the productivity and depreciation gains are small, while the cost is fixed, indicating that the present value of benefits is unlikely to exceed the costs. As time passes the likelihood of net gain increases, as the productivity of the available leading edge technology begins to far exceed that of the existing, increasingly depreciated capital.

If there are quadratic costs and serially correlated productivity shocks in the CHP framework, the dynamics of capital adjustment are quite different. The smoothing response to quadratic costs and serial correlation in productivity yields serial correlation in investment. If productivity shocks have a very high variance, investment spikes can take place, but they would occur in bunches. This implies that the probability of large investment this period is higher if there was an investment spike in the previous period, or that the hazard would be downward sloping. Note also, that zero investments would be very hard to explain in the CHP model with quadratic costs. Firm investment would respond to any productivity shock, however small. Zero investment would only be optimal when the firm's demand for capital has decreased precisely as much as the capital stock has depreciated.

To summarize, these two particular fixed cost adjustment models suggest two empirical approaches. The CE model yields predictions about the average size of investment as a function of imbalances between desired and actual capital. The CHP model has implications for the probability of investing over time, as a function of the past investment history. We have also seen that for the CHP model with quadratic costs, the hazard for the probability of investing over time would be different. We will examine firm investment behavior along these two dimensions: adjustment in imbalance state, and adjustment in temporal state.

In Figure 1, the first column refers to quadratic costs, the second to piecewise linear (a particular type of kinked adjustment cost) and the third to fixed costs. The panels in the first row depict optimal demand for capital over time if there were no adjustment costs, where there are stochastic shocks to the investment fundamentals, and optimal demand under the three adjustment cost structures (from Hamermesh and Pfann, 1996).[14] As shown in the first panel, with symmetric quadratic costs, the actual path of capital exhibits less variation than would be observed if adjustment costs were zero and capital followed the dynamic path implied by the vector of forcing variables alone. The second column considers piecewise linear costs, where the costs of positive investment are greater than disinvestment. In a forward-looking investment decision, these costs generate periods where optimal capital does not vary, even though the fundamentals are changing. This inaction occurs because firms do not wish to incur the adjustment costs of adding to the capital stock if in the near future they would find it necessary to incur the cost again when fundamentals turn downward. Finally, the third column illustrates the dynamics of capital with fixed costs. Only large changes in the

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[14]For simplicity, it is assumed that agents have perfect foresight and that capital does not depreciate. However, the general mechanics demonstrated in Figure 1 are not altered by adopting more realistic assumptions regarding expectation formations and capital depreciation.

the third column illustrates the dynamics of capital with fixed costs. Only large changes in the fundamentals lead the firm to change capital. When the firm does decide to change capital, the adjustment costs are sunk, and it makes a large change.

The second row of Figure 1 graphs the dynamics of the investment to capital rate derived from the path of capital under the three adjustment cost structures. This row relates to one of the dimensions of investment behavior we will examine: the probability of investing over time as a function of past investment history. The figure shows the smooth path of the investment rate under quadratic costs, and the periods of inaction interrupted by investment spikes with fixed costs. As in the CHP model, these paths for the investment rate would be consistent with the downward and upward sloping investment hazard, respectively. The second column depicts the dynamics of the investment rate under piecewise linear costs. There are periods of inactivity, or zero investment, interspersed with periods of positive investment, where the investment rate varies gradually. Under this adjustment cost structure, the probability of investing will be higher if a firm has invested in the recent past. Thus, similar to quadratic costs, there will be positive correlation in investment decisions over time, implying that the probability of investing is a decreasing function of the time since the last investment, or a downward-sloping hazard.

For the three adjustment cost structures, the third row of Figure 1 depicts the average investment rate as a function of mandated investment, the difference between desired and actual capital (from Goolsbee and Gross, 1997). This is the second dimension of investment behavior that we will examine. The relationship is linear under quadratic costs (as firms close a constant part of the gap between desired and actual capital each period), and linear with a region of inaction for piecewise linear costs. The figure for non-convex costs is similar to those from the CE model: a region of inaction and a nonlinear function, where large deviations of actual from desired capital lead to proportionately larger changes in investment than small deviations.

To summarize, we have seen that in the temporal dimension both piecewise linear and quadratic costs yield a downward sloping hazard, whereas fixed costs result in an upward sloping hazard. Furthermore, in the imbalance state, both piecewise linear and fixed costs lead to an inaction range, whereas quadratic costs do not. Hence, in order to differentiate between the three adjustment cost structures, it is necessary to examine adjustment in both imbalance state and in the temporal state. This is the premise for the empirical analysis below.

B. Empirical Evidence

A number of recent papers exploring irreversibilities and non-convex adjustment costs in firm investment were motivated by the striking patterns of capital accumulation in the U.S. manufacturing sector, documented by Doms and Dunne (1997). Using a Census Bureau 17-year panel of over 13,000 firms, they find that: (i) over half the plants in the sample experience capital growth of at least 37 percent in a single year; (ii) a significant portion of a plant's gross investment over the 17-year period is concentrated in a single year;

and (iii) periods of large aggregate investment are partly due to changes in the frequency of plants undergoing large investment episodes, or investment "spikes."

Similar patterns have been documented using large firm data sets for Norway (Nilsen and Schiantarelli, 1998) (NS), and Mexico and Colombia (Gelos and Isgut, 1999) (GI). Both studies find that while a sizable fraction of investment may be characterized as maintenance investment, large investment spikes account for a significant proportion of total investments. The studies also show that the share of zero investment episodes is very high.[15]

For two industrial countries, as well as two developing countries, the descriptive statistics offer strong support that firm level investment is intermittent and lumpy. To date, however, efforts to confirm the empirical implications of both the CE and CHP fixed cost models have met with mixed success. In general, although a number of authors have claimed that their results provide evidence for both irreversibilities and non-convex (specifically fixed) adjustment costs, our impression is that the first type of friction is much more strongly supported in the results than the second.

Goolsbee and Gross (1997) estimate non-parametric kernel regressions of investment as a function of the difference between desired and actual capital (both logged), using a panel of firms in the U.S. airline industry and disaggregated data on heterogenous types of capital. The average investment function has a flat portion for negative and low levels of mandated investment, and a positively sloped, linear portion as mandated investment increases. The authors find this consistent with irreversibilities, or large costs of disinvestment, and quadratic costs conditional on positive investment. We assume that the claim "the results show clear evidence of non-convex adjustment costs" refers to costs of disinvestment. GI also present nonparametric estimates and find a very similar pattern for Colombia and Mexico.

Using the U.S. Census Bureau's Longitudinal Research Database, Caballero, Engel and Haltiwanger's (1995) (CEH) plots of average investment as a function of mandated investment illustrate a similar asymmetric response to positive and negative mandated investment. The authors' note that the convex shape of this plot supports models with fixed costs of adjustment. It appears, however, that most of the nonlinear relationship stems from average investment's weak response when mandated investment is negative.[16]

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[15]While most important at the plant level, for small firms, and for the buildings and land component of investment expenditure, there are zero investment episodes at different levels of aggregation (plant and firm), firm size classes, and type of investment activity.

[16]Woodford (1995) questions whether a similar plot could also obtain if firms face convex adjustment costs, but if the marginal profits associated with capital stock increases were very steep at low levels of the capital/output ratio. In general, while he finds the CEH microeconomic evidence supportive of irreversibilities, he does not agree that there is

(continued...)

Moving on to empirical tests of the CHP model, the evidence is just as mixed. Using a method that controls for unobserved heterogeneity, for the U.S. manufacturing sector CHP find that the hazard slopes down for one period, and then slopes up. They explain the first feature by the fact that the expenditures for a large investment project may be recorded for two consecutive calender years, although they are part of the same investment. The upward sloping portion of the hazard is supportive of a model with fixed adjustment costs. However, since the coefficients indicate that the hazard is basically flat after the fourth duration (time between spikes), it would have been helpful for the authors to test whether the flat hazard restriction could be rejected, and discuss these results.

For Norway, although NS claim to have found a J-shaped hazard (after an initial fall in the first period) the pattern actually appears not at all smooth or monotonic. Using similar estimators, GI find downward-sloping hazards for the Mexican case, and essentially flat hazards for Colombia.

III. Data and Descriptive Statistics

The data are derived from surveys in Cameroon, Ghana, Kenya, Zambia and Zimbabwe as part of the Regional Programme on Enterprise Development (RPED), organized by the World Bank during the early and mid 1990s. Each survey round covered approximately 200 firms, who were subject to in-depth interviews on issues relating to current and past performance and the business environment. Large as well as very small firms, including informal ones, are represented in the sample. The firms are drawn from four manufacturing sub-sectors: food, wood, textiles and metal. Together, they represent the bulk of manufacturing output in the three countries. Three survey rounds were carried out in each country, and data are annual. The contemporaneous data span the following periods: Cameroon, 1993-95; Ghana, 1991-93; Kenya, Zambia and Zimbabwe, 1992-94. Retrospective information enables us to construct longer time series than three years for certain variables, including investment. A total of 1208 firms have been surveyed at least once. We have discarded firms with too few observations over time and a few outliers, yielding a sample size of 821 firms, which we will refer to as the "full sample" throughout the analysis. For details about sample selection and construction of variables, see Data Appendix.[17]

The first thing we examine is the extent to which firms have episodes of zero investment. In a quadratic cost model firms make small, continuous and partial adjustments to all shocks and zero investments are very difficult to explain. As discussed above, however, inactivity, or no investment in particular periods can be optimal in models with either fixed

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[16](...continued)
compelling evidence for lumpy adjustment as predicted by fixed cost of adjustment models.

[17]Note that all surveys oversampled large firms. In recognition, we control for differences between firm size categories in most of the empirical analysis.

costs or irreversibilities. Thus, evidence of many zero investment episodes for an important share of firms tends to cast doubt on the applicability of quadratic adjustment costs.

In Table 1 we report the proportion of firms making any investment during a year within the sample period, by country and for four size classes. The share of firms in the entire sample making some investment during a year is less than one half. Thus, 58 percent of the observations (firms in a given year) are zero investment episodes. The propensity to invest is positively related to firm size. The low investment propensity in Cameroon and Ghana and the high propensity in Zimbabwe can largely be attributed to differences in the size distribution of firms. In Table 2 we report proportions of firms ever selling capital goods during the sample period.[18] Confining attention to disinvestments larger than 10 percent of the capital stock, there is an unanimous picture of capital sales of this relative magnitude being extremely unusual. Less than 2 percent of all sampled firms ever have a disinvestment rate in excess of 10 percent.

Having found that a significant share of the firms refrain from investing during an entire year, we proceed by examining whether firms compensate by making relatively large, or lumpy, investments once they decide to act. The distribution of firms' investment rates is reported in Tables 3 and 4, along with the contribution of each investment rate category to total investments in the sample.[19]

First, note that the largest proportion of the observations (firms in a given year) have investment rates less than 10 percent, implying that small maintenance and replacement investments are an important part of investment activity.[20] However, we also observe that 27 percent of the observations have investment rates larger than 20 percent, which suggests that disequilibria in capital stocks may be substantial for a non-negligible number of firms. For 14 percent of the observations, when they invest, their investment to capital rate is over 40 percent, and this 14 percent of the observations makes up 26 percent of the total investment in the sample. This provides some evidence for the lumpiness of investment. This result is more pronounced for small firms (Table 4): 32 percent of the observations of investing small firms have investment rates larger than 0.2, compared to 25 percent for large firms. Furthermore, the share of large firms making the lowest replacement and maintenance investments is larger than that of small firms.

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[18]The sample period refers to the three years with contemporaneous data, see above.

[19]Data on investment and capital have been converted to real 1991 U.S. dollars to ensure comparability across countries and over time periods.

[20]NS note that while the large fraction of observations with small positive investment rates may seem inconsistent with non-convex adjustment costs, it is reasonable if we assume that adjustment costs for replacement investment are very small, and fixed costs are relevant only for expansion investment.

Figure 2 shows the histogram of standardized investment/capital rates (for investing firms only), calculated by subtracting the firm level mean and dividing by the standard deviation. The distribution of firm investment rates exhibits skewness and kurtosis. CEH also find a non-normal distribution of investment rates in the U.S. manufacturing sector and note that since fat tails indicate a large fraction of large investments, these plots are supportive of non-convex adjustment costs.

Although Tables 3 and 4 tell us that on average a significant fraction of observations are relatively large investment rates, these data cannot be used to determine whether investment spikes are important for individual firms.[21] To further assess the extent to which firms made infrequent but relatively large investments, we follow the method initiated by Doms and Dunne (1997). We rank each firm's investment rates over time from the highest (rank 1) to the lowest (rank 5), and compute the average investment rates for each rank and the share of each rank in a firm's total investments.[22] Table 5 shows that the average investment rate of the highest rank is almost than three times higher than that of the second highest, and seven times higher than that of rank 3.The investments associated with the largest investment rate for each firm represents 50 percent of total investments, which further underlines the considerable importance of lumpy investments at the firm level for aggregate investments.[23] We have also looked at the mean investment rate for each rank separately for small and large firms (not reported). As expected, these results indicate that the highest ranked investment rate accounts for a larger share of total investments for small firms than for large firms, consistent with other evidence that investment tends to be lumpier for small firms.

Finally, to document the degree of persistence in investments we have calculated the average investment rates one year before and after observations for each rank. The results also lend support to characterizing firm investment as lumpy since the average investment rates in the years immediately before and after the firm's highest investment are conspicuously low. The mean investment rate in the years before and after the highest rank is on average less than one fourth of the investment in the year of the highest rank. In contrast to the highest rank, however, there does seem to be some degree of persistence for the lower ranks.

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[21]It could be consistent with either a few firms always making large investments, or many firms occasionally have large investments.

[22]Only firms with at least five years of observations were included in these computations.

[23]The average investment rates are for a five year period. Our results are similar to other studies. Doms and Dunne (1997) find that 50 percent of total investment over a 16 year period is contributed by the highest three ranks; NS report that 46 percent of total investment over a 14 year period is accounted for by the highest three ranks; and GI(1999) find that investment episodes in the highest three ranks account for 58 percent of total investment in the Mexican sample (11 years) and 61 percent in the Colombian sample (eight years).

We have found that both zero investment episodes and lumpy investment appear to be more important for small firms. This result appears plausible, for a number of reasons. First, the indivisibility of capital goods is another factor that could contribute to lumpiness. Indivisibility leaves the firm with a choice of making a large investment or no investment at all. Since indivisibility sets a lower limit on absolute, rather than relative, investments, one would expect small firms to be more severely affected by indivisibility problems than large firms.[24] Second, the intermittent, lumpy character of investment could be smoothed in large firms by the aggregation of different types of production processes that occur. Third, small firms tend to face greater credit constraints (Bigsten et al, 1999), which could prevent firms from making any investment in particular periods.[25] NS note that small firms' larger degree of lumpiness is consistent with fixed costs that do not depend on firm size, but not with those where the fixed cost component increases with the size of the capital stock.

We also explore the relation, for each year, between the proportion of firms having their highest rank investment and the aggregate investment rate. The aggregate investment rate for each year is the sum (in constant U.S. dollars) across all firms in the sample in a given country. The results of a regression of the log of the sample aggregate investment rate on the proportion of highest ranked investment rates is shown in Table 6. An increase in the proportion of firm's experiencing an investment spike—their highest-ranked rates—significantly increases aggregate investment. A one percentage point increase in the share of firms experiencing an investment spike implies a 5 percent increase in the aggregate investment rate.

The results discussed in this section indicate that investment activity takes the form of large adjustments concentrated in a few periods. These descriptive statistics are consistent with an adjustment cost technology featuring non-convexities, and in little accordance with quadratic costs. We have also shown that fixed costs have important implications for the evolution of the aggregate capital stock, since firm level lumpiness is a significant factor driving aggregate investments.

IV. Econometric Analysis

A. Nonlinearities in the Investment Function

In CE's model with non-convex adjustment costs, a firm's average investment is an increasing function of the difference between desired and actual capital, termed mandated investment. If adjustment costs are quadratic, the relationship is linear. We examine this

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[24]The fact that lumpiness is still important for large firms argues that fixed costs are also important, since, as opposed to indivisibilities, the firm cannot grow our of these frictions.

[25]As we argue below, however, precautionary savings arguments regarding internal finance could have an opposing influence, leading to less lumpiness for financially constrained firms.

function using both a parametric and a non-parametric method.

CEH define mandated investment as the deviation between desired and actual capital:

$$(I/K)_{it}^{MANDATED} = \tilde{k}_{it} - k_{i,t-1}$$

where $\tilde{k}_{it}$ and k_{it-1} are the log of desired and actual capital. Desired capital, the stock that firms would hold if adjustment costs were temporarily removed, is equal to frictionless capital, the stock that firms would hold if they never faced adjustment costs, plus a firm specific constant.

Like other authors, our estimation of desired capital is likely to be quite imprecise. A number of simple neoclassical models with perfect competition and constant returns to scale yield an expression for frictionless capital that is a function of output and the cost of capital. We do not have an adequate measure of the firm's user cost of capital, but since this can be expected to be slow changing, we use a fixed effects approach to eliminate this variable.[26] Since desired capital equals frictionless capital plus a firm-specific constant, we can estimate desired capital as a function of output and a firm specific constant using fixed effects. We impose no restrictions on the output elasticity.

Desired capital, the left-hand side variable in the first step regression, is not observable. We follow CEH and GI in arguing that deviations between desired and actual capital are likely to be stationary over time. This implies that we can use the actual capital stock series and interpret the regression as determining long-run desired capital. Our measure of firm's desired capital is the predicted value from this regression.[27]

The second step is to estimate the firm's investment to capital rate as a function of mandated investment, the log deviation of desired and actual capital stocks. We use both a non-parametric and a parametric method. First, following Goolsbee and Gross (1997), we use a Nadaraya-Watson kernel estimator which puts very little restriction on the shape of the function. What do these nonparametric estimates imply about the nature of adjustment costs? One feature that other authors have explored is whether a range of inaction, which would show up as a flat segment of the estimated curve, can be identified. Recall that a flat segment

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[26]Bond and Meghir (1994) also follow this approach. We also experiment with using the profit rate as a proxy for the user cost of capital. Given that most firms in our sample are financially constrained and rely largely on internal funds to finance investment, this is more relevant than lending rates. The results were very similar.

[27]With this approach the scale of the imbalance state is not identified, since desired capital (unobserved) differs from frictionless capital (computed) by a constant. Therefore, it would not be inconsistent to observe, say, an increasing function for negative values of mandated investment. The fact that the scale is unidentified is not important, since it is the *shape* of the function that is informative of the adjustment cost structure.

would be consistent both with a model with piecewise linear costs (or irreversibilities), and with fixed adjustment costs. For reasons discussed above we focus on the CE representation of fixed costs, i.e. that fixed costs are stochastic. This yields a nonlinear relationship between mandated investment and average investment rates; the average response to large disequilibria should be proportionally larger than the response to small disequilibria.

Figures 3 and 4 plot the nonparametric regressions for each country separately, and pooled over all countries, respectively. The results are quite mixed. For Cameroon, Kenya and Zimbabwe, the average investment rate is a convex function of mandated investment. In Kenya, average investment increases substantially for firms with the largest disequilibria. In Cameroon and Zimbabwe, the slope increases more gradually over the range of mandated investment. For Ghana and Zambia, however, the plots are non-monotonic and the patterns are not reasonable with any specification of adjustment costs. The confidence intervals indicate that the estimates are less precise at very large disequilibrium levels, which is to be expected since there are relatively few data points at these levels. When pooling all countries (Figure 4) we obtain a convex function, which is more precisely estimated than the country specific estimates.

We compare these nonparametric estimates to a parametric approach where we regress firm's investment rates on mandated investment and mandated investment squared. OLS results, with zero investments included, are reported in Table 7. Since residuals are likely to be non-normal due to the inclusion of zeroes in the dependent variable, and since the imbalance measure is a generated regressor, one should be interpret the reported standard errors with a great deal of care, and the regression results should primarily be viewed as descriptive statistics. Nevertheless, there are considerable differences in the estimated standard errors across countries. A significant squared term would be indicative of nonlinearities in the investment function. Here, the squared term is not "significant" for Cameroon and Zambia, but for Ghana, Kenya, and Zimbabwe it is. We therefore conclude, tentatively, that for Cameroon, Kenya, Zimbabwe and possibly Ghana, the estimates support models with non-quadratic adjustment costs.

B. The Shape of the Hazard Function

CHP's fixed cost model predicts that the probability of investing increases as the time since the last investment increases, i.e. an upward sloping hazard. In order to test this hypothesis, it is critical to employ an econometric framework which enables us to isolate the structural effect of past investment decisions. The effort to achieve this objective raises a number of econometric issues, which we discuss below. These include: (i) the importance of controlling for unobserved heterogeneity; (ii) the greater suitability of a random effects relative to a fixed effects approach; (iii) the estimation of a random effects model when the distribution of the random effect is not parameterized, but is assumed to be discrete with a limited number of support (mass) points; and (iv) the importance of addressing the problem of initial conditions.

We will employ two types of econometric methods in our empirical analysis: logistic hazard models and dynamic panel logit models. In addition to non-parametric sample hazards and logistic hazards with no unobserved heterogeneity, we will estimate logistic hazards with nonparametric random effects. This latter model addresses the first three econometric issues, and has been used in the studies on the United States, Norway, Colombia, and Mexico. The dynamic panel logit model, which has not been employed in this literature, is a framework that also addresses these issues, as well as the problem of initial conditions. Below, the four issues are discussed in a fashion general enough to be applicable to both the logistic hazard and dynamic logit methods. More detail will be offered in further development of each type of model (Section 4.3).

What types of econometric methods enable us to isolate the structural effect of past investment decisions? Although controlling for observed heterogeneity accomplishes some of this objective, it can also be anticipated that there exist unobserved characteristics that affect the investment probability.[28] If these variables are slow changing, previous investment may appear to be a determinant of future investment simply because past investment is correlated with omitted variables. In this case, neglecting unobserved heterogeneity will yield spurious correlation between past and future investment, in the sense that the observed positive correlation is due to omitted variable bias, rather than to behavioral mechanisms.[29]

These considerations show that it is important to control for unobserved heterogeneity. This can be quite complicated in a dynamic discrete choice model, however, since the non-linearity typically inherent in discrete choice models rules out many of the panel procedures routinely implemented in linear models. In what follows we seek to provide the reader with the intuition behind our modeling strategy in Section 5.[30]

A general formulation of a dynamic binary choice model can be written:

$$y_{it} = 1\,[\beta_1^{\prime} x_{it} + \beta_2^{\prime} y_{i,t-1}^{S} + \eta_i + v_{it} \geq 0], \quad t=1,2,\ldots,T \tag{1}$$

where y_{it} is the outcome of the binary choice in time t, $1[.]$ denotes the indicator function, β_1 is a vector of coefficients associated with the set of strictly exogenous explanatory variables

[28]Differences in managerial ability, access to technology, productivity, and capital depreciation rates, are only a few examples.

[29]See Heckman (1981a) for a discussion on the distinction between true and spurious state dependence.

[30]It should be stressed that, for ease of exposition, we will leave out several statistical details and subtleties, most of which can be found in the original sources which we draw on. It should also be borne in mind that if unobserved heterogeneity is absent, the estimation of a dynamic binary choice model is no more difficult than estimating a standard cross-section model, since observations will be independent over time and can therefore be pooled.

x_{it}, and β_2 contains coefficients associated with a vector of S lags of the dependent variable, denoted by $y^S_{i,t-1}$. Further, η_i represents unobserved heterogeneity, and v_{it} reflects transitory errors which are uncorrelated over time.

As usual in panel data, an important distinction is related to whether η_i is assumed a fixed (nonstochastic) constant for each firm, or randomly distributed across firms. Perhaps the main advantage of assuming fixed instead of random effects is that, under fixed effects, dependence between the firm specific effect (e.g. managerial ability) and any explanatory variable (e.g. profit) is considerably more easy to handle. Under random effects such dependence would necessitate specifying the marginal distribution of the random effect, given the explanatory variable. This can be rather difficult in practice, even for only one explanatory variable. On the other hand, a major disadvantage of the fixed effects model is that, for specifications with a reasonable number of exogenous variables, consistent estimates requires either T or N to be very large. For small T, the problem of incidental parameters will cause biased estimates if firm dummies are used to control for the fixed effects. Under certain conditions this problem can be avoided by a conditional logit approach outlined in Chamberlain (1985) and extended by Honoré and Kyriazidou (1997), but the inclusion of strictly exogenous variables will typically require semi-parametric methods which are unlikely to work well unless N is rather large.

For these reasons we will focus on random effects models throughout the analysis. Under random effects, the probability of observing an investment in time t can be written

$$(2) \qquad Pr(y_{it}=1|x_{it},y^S_{i,t-1},\eta_i)=F[\beta_1'x_{it}+\beta_2'y^S_{i,t-1}+E(\eta_i|y^S_{i,t-1})]$$

where F denotes the cdf of the distribution (assumed symmetric) of the transitory error v_{it}, and where the argument of F is normalized by the standard deviation of v_{it}. It follows that the individual likelihood is equal to:

$$(3) \qquad L_i = \prod_{t=1}^{T} F[(\beta_1'x_{it}+\beta_2'y^S_{i,t-1}+E(\eta_i|y^S_{i,t-1}))(2y_{it}-1)]$$

In order to estimate the parameters of interest in (3) it is necessary to integrate η_i out of the likelihood. In the special case where the analyst has data from the very beginning of the data generating process, or if the process is in equilibrium at the initial time of observation, integrating (3) over η_i yields the relatively straightforward form

$$(4) \qquad L_i = \int \prod_{t=1}^{T} F[(\beta_1'x_{it}+\beta_2'y^S_{i,t-1}+\eta)(2y_{it}-1)]\,dG(\eta)$$

where $G(.)$ denotes the distribution of the random effect. However, if the analyst does not have access to the process from the beginning, and the process cannot be assumed to be in equilibrium at the initial time of observation, integrating over the random effects distribution yields a different expression:

$$(5) \qquad L_i = \int \prod_{t=1}^{T} F[(\beta_1' x_{it} + \beta_2' y_{i,t-1}^{S} + \eta)(2y_{it} - 1)]\, \psi(y_{i0}^{S} | \eta)\, dG(\eta)$$

where $\psi(.)$ denotes the marginal probability of the initial state $y^S_{i,t-1}$, conditional on the random effect (see e.g. Hsiao, 1986, p. 170). This is a considerably more complicated likelihood to maximize than (4), but unless the initial condition of the lagged endogenous variable can be assumed independent of the random effect, consistent estimates cannot be obtained by maximizing (4) unless T is very large.[31]

In the dynamic panel logits[32], we start with likelihoods such as equation (5), where we address the initial conditions problem. As noted, when we do not have data from the very beginning of the data generating process, the random effects will be correlated with the lagged dependent variable.[33] Thus, we need to address the fact that the initial lags in our sample are not independent of the random effect.

It is common in the literature to assume some parametric form for the distribution of the random effect. We instead adopt a non-parametric approach along the lines suggested by Heckman and Singer (1984), and approximate $G(.)$ as a mass point distribution with a finite number of support.[34] This implies that (4) and (5), respectively, can be rewritten as

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[31]This is the problem of initial conditions in dynamic panel data models. See Heckman (1981b) or Hsiao (1986) for a thorough discussion.

[32]The logit model assumes that $F(z)=(1+\exp(-z))^{-1}$, where z is the index.

[33]In our case, assume the firm started operating in period 0, and made choices to invest or not in periods 1, 2 and 3. Our model says that there is a random effect in every period. If our data only starts in period 2, however, we would run a regression on the investment status in period 3 as a function of status in period 2, together with other correlates. The problem is that the random effect will have affected investment status in period 2 (which we did not observe) and since the random effect is the same in period 2 and period 3, when we run the model in period 3, there will be correlation between the regressor, investment status in period 2, and the random effect. This violates the assumption that the correlation between the regressors and the random effect is zero.

[34]For an empirical application of this nonparametric strategy to a dynamic logit model, see Moon and Stotsky (1993).

(4') $$L_i = \sum_{m=1}^{M} \prod_{t=S}^{T} H_{it}(e_m)^{y_{it}} [1 - H_{it}(e_m)]^{(1-y_{it})} Pr(\eta_i = e_m),$$

(5') $$L_i = Pr(y_{i0}^S) \sum_{m=1}^{M} \prod_{t=S}^{T} H_{it}(e_m)^{y_{it}} [1 - H_{it}(e_m)]^{(1-y_{it})} Pr(\eta_i = e_m | y_{i0}^S = w),$$

Further, w is a vector of outcomes, e_m, m=1, 2,...,M, are M points of support, and the associated probabilities are parameters to be estimated.[35] In Section 5 we will form the basis of our analysis on likelihood forms like (4') and (5').

where $$H_{it}(e_m) = F(\beta_1' x_{it} + \beta_2' y_{i,t-1}^S + e_m).$$

There are two main reasons why the nonparametric assumption for the random effect is appealing. First, as shown by Heckman and Singer (1984), estimation results may be highly sensitive to incorrect parametric assumptions for the random effect, and a nonparametric approach is much more flexible. Second, in the case of the dynamic logit model, it is one way to address the initial conditions issue. Since the initial lags are not independent of the random effects, Arellano and Carrasco (1996) suggest conditioning the mass point probabilities on the random effects. This is feasible when the random effect has finite support. It is not feasible, though, when the random effects are normally distributed, for example. In this case it would be necessary to compute an infinite number of conditional probabilities, since there are an infinite number of possible values for the random effect.[36]

C. Transition Data Models

Hazard models

We estimate hazard models both for the probability of a firm investing and the probability of a firm having an investment spike, defined below. For simplicity, we use the

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[35]The decomposition in (5') is due to Arellano and Carrasco (1996). The initial conditions of the process are left unrestricted, and the associated probabilities in the vector $Pr(y_{i0}^S)$ are parameters to be estimated (see Section 5).

[36] Therefore, one needs an alternative strategy for dealing with the initial conditions problems if the random effects are assumed normally distributed. Heckman (1981b) and Roberts and Tybout (1997) propose modeling the initial conditions. The drawback of this approach is that a few years of the panel are lost to the initial conditions modeling, which is quite costly in short panels such as ours.

term investment spikes in the exposition. Following the notation of NS, the hazard can be written as:

$$p_{it} = Pr[T_i = t \mid T_i \geq t, t - (T_{i-1} + 1), x_{it}] \tag{6}$$

where T_i represents the time at which firm I has an investment spike, $t - (T_{i-1} + 1)$ the time since the last investment or spike, and x_{it} a vector of additional predictor and control variables.[37] As a preliminary step, we estimate nonparametric sample hazards. With no assumptions about the distribution of the error term, this estimator calculates the hazard of a spike as the number of spikes in the sample divided by the number of firms that could have had spikes, i.e. those that had yet not had spikes up to that time. The sample hazard has several weaknesses, most importantly that the only way to control for heterogeneity across observations is to estimate separate hazard functions for each sub-group.

We have discussed above the difficulties of controlling for heterogeneity in dynamic discrete choice models. The first approach we take is a model which controls for observed, but not unobserved, heterogeneity. Parameterizing the hazard as a logistic function represents the log-odds of a firm having an investment spike as a function of duration dummies representing the time since the last spike, and of other predictors. d_{sit} is a set of duration dummies equal to one if the last spike occurred s periods ago, zero otherwise. The model yields a baseline hazard of the probability of a spike conditional on the time since the last spike. The family of logit-hazard profiles represented by all possible values of the predictor and control variables are parallel and share a common shape, being vertically shifted for different values of the predictor and control variables. The model can be written as:

$$p_{it} = \frac{1}{1 + \exp[-\sum_{s=0}^{S} \gamma_s d_{sit} - \beta' x_{it}]} \tag{7}$$

where S denotes the longest duration of spells of no investment spikes. P_{it} represents the conditional probability that y_{it} equals one, where y_{it} is an indicator variable that equals one if a firm has an investment spike in period t, zero otherwise. A number of papers have derived the log-likelihood function for this model and shown that it is equivalent to a binary logistic regression with time period indicators d_{sit} and covariates x_{it} (see Allison, 1982, for example). The log-likelihood can be written as:

$$\log L = \sum_{i=1}^{N} \sum_{t=1}^{T_i} y_{it} \log(P_{it}/(1-P_{it})) + \log(1-P_{it}). \tag{8}$$

[37]Throughout the analysis, T and t refer not to calendar time, but to the length of the inaction period.

As a baseline, we report the estimates from the logistic hazard models. Then we extend the logistic hazard to allow for unobserved heterogeneity. We follow Heckman and Singer (1984), and introduce a random effect v_i assumed to be independent of the explanatory variables and distributed according to an unknown distribution function. As discussed in Section 4.2, it is necessary to integrate over the distribution of v in order to obtain the unconditional likelihood. Adopting the non-parametric strategy in which the unknown distribution of v is approximated by a distribution with a discrete number of mass (support) points, the likelihood function can be written as (see equation (4') above):

$$\log L = \sum_{i=1}^{N} \log \sum_{v=1}^{M} pr_v \prod_{t=1}^{T_i} P_{itv}^{y_{it}} (1 - P_{itv}^{(1-y_{it})}) \tag{9}$$

where P_{itv} is the logistic probability allowing for a random effect, M is the number of mass points, determined by increasing the number of points until the likelihood fails, and the pr_v's are the associated probabilities.

Dynamic panel logits

Although the hazard models have several advantages, perhaps most importantly that it allows for a long duration dependence with few restrictions on shape of the hazard, there are also some drawbacks.[38] It is not possible to include firms whose inactivity durations are left censored (arising whenever the start of the duration is unobserved), a problem which becomes acute when investment spikes are analyzed. Unfortunately, because left censored observations are likely to be long spells, this omission may bias the estimated duration dependence upwards. Further, we include only one contiguous period of inactivity per firm in order to guard against bias arising from the fact that the pooling of all spells would result in a

$$y_{it} = \begin{cases} 1 & if \quad \beta_1' x_{it} + \beta_{21}' y_{i,t-1} + \sum_{j=2}^{J} \beta_{2j} [y_{i,t-j} \prod_{k=1}^{j-1} (1 - y_{i,t-k})] + \eta_i + v_{it} \geq 0 \\ 0 & otherwise \end{cases} \tag{10}$$

disproportionately large number of short durations. This implies that we disregard information related to the time after a firm's duration has terminated, which is inefficient. Finally, we are unable to account for the fact that initial conditions are in fact endogenous.

[38]We include nine duration dummies, or spells of up to nine years of investment inactivity. Allowing for long duration dependence might be important if elements of convex costs, or other factors lead to a downward sloping hazard over some range and an upward slope for long duration dependence.

Many of these shortcomings can be addressed in a dynamic panel logit framework. This approach requires restrictions on the duration dependence (specifically, the data generating process is required to be duration independent after s years, where s is the number of lags in the logit specification). We parameterize the panel logits as follows:

where it is assumed that v_{it} is independent identically distributed logistic disturbance term (see footnote 30). We will return to the choice of lag length below. Note that the summed expression in (10) summarizes the firm's most recent investment experience: whenever $y_{i,t-s}$=1, then the terms within [ ] will be zero for all $u>s$. Thus, this lag structure is similar to that implied by the hazard models discussed above.

V. Empirical Results of Transition Data Models[39]

This section reports empirical results of the transition data estimators described above. Throughout the analysis we maintain two definitions of the "event" we are modeling: whether or not the firm made any investment at all during the year, and whether or not a firm made a sufficiently large investment to constitute an investment "spike". Following CHP and NS, we define an investment spike as an investment/capital rate exceeding 0.10. Only equipment investment is considered. Since hazard estimation of the type employed here requires data on the start of the duration, left censored observations (i.e. firms with a history such as the following: {0,0,0,1}) cannot be included in the analysis. Therefore, the number of firms used in the analysis will be smaller than the full sample of 821. The problem of left censoring is more acute in the spike models. Here, a firm history such as {1,0,0,1}, where 1 equals positive investment may become {0,0,0,1} when the event of interest is a spike, if the first investment was small. Estimation of the probability of spikes will therefore be based on yet fewer firms.[40]

[39]All models in this section were estimated in STATA 6.0 (StataCorp., 1999). Routines for estimating the nonparametric maximum likelihood (NPML) models were coded using the ml command in STATA. The likelihood functions of the NPML models are not globally concave, implying that convergence may occur at local maxima. We guard against this by using several different sets of start values.

[40]This is less of a problem for CHP, NS and GI, all of whom have much larger numbers of firms in their data sets.

We begin by reporting non-parametric estimates of the sample hazard.[41] In Figures 5 and 6, we show disaggregated hazard estimates according to country and firm size, for non-zero investment, and spikes, respectively. Two size classes are considered: small firms are those with 20 or less employees, and large firms have more than 20 employees. One general result in all five countries is that the estimated hazard probabilities decrease over time, until very few observations remain in the risk set, thus making the estimates imprecise. The hazard estimates for Ghana, Kenya and Zambia are quite similar in magnitude, given the duration. Cameroon is associated with lower hazard estimates than the other countries, whereas the initial hazard estimates of Zimbabwe are considerably higher, but more quickly falling, than in the other countries. This means, for example, that the probability of investing as a function of the duration dummies and other controls is everywhere lower for Cameroon. In Table 8 observations are pooled across countries and size categories. The log-rank test of the hypothesis that hazard functions are common indicates that pooling is not overly restrictive.

The message from the results in Figures 5 and 6, and Table 8 is clear: there is no evidence of upward sloping hazard functions in our sample, neither for non-zero investments nor for investment spikes. This is in accordance with the predictions of the quadratic adjustment costs model and not consistent with the fixed costs model. However, we should remain skeptical of this result, since the negative duration dependence may be due to omitted heterogeneity. Therefore, we now turn to parametric models, and attempt to account for some observed and non-observed heterogeneity across firms.

Table 9 presents the results of the logistic hazard models discussed in Section 4.3.1. In all models that follow we include the following additional predictor variables to partially account for firm heterogeneity: firm age, (log of) size, the profit rate, and the change in

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[41]All results reported below are based on annual duration intervals. It may be the case that the fixed costs that firms incur, rather than being applicable to investment in a given year, are applicable to any investment made in a longer, say two-year horizon. Are results sensitive to this degree of temporal aggregation? To explore this issue, we have estimated all models with bi-annual duration intervals as well. Results, which were similar to their annual counterparts, are available upon request from the authors. In fact, the insensitivity of the results to temporal aggregation is in accordance with the results of Bergström and Edin (1992) and Sueyoshi (1992). Bergström and Edin used unemployment data and found that discrete models were less sensitive to temporal aggregation than continuous-time models, concluding that for discrete models the stability of parameter estimates associated with the regressors was "remarkable" (p. 16). The estimates of the hazard probabilities were somewhat more sensitive to aggregation, although this primarily affected the vertical position of the baseline rather than the shape, which remained stable. Sueyoshi reported Monte Carlo simulation results indicating that the estimates of the hazard shapes were "relatively insensitive to the degree of aggregation" (p. 38). Again, bias from aggregation led to vertical shifts in the estimated hazard function, rather than altering its shape.

employment (as a proxy for accelerator effects), as well as country and sector dummies.[42] Details about variable definitions and descriptive statistics are provided in the Data Appendix. The coefficients on the duration dummies are monotonic transformations of the baseline hazard function, and since the model is estimated with an intercept we have excluded the duration dummy for the shortest interval. Hence, negative signs on the coefficients associated with d1-d9 indicate that the hazard function is lower than in the first year after investment, and decreasing coefficients means that the hazard function is decreasing. The ML model does not allow for unobserved heterogeneity, whereas the NPML (nonparametric maximum likelihood) model allows for random effects of the discrete Heckman-Singer form.

Turning first to the models without unobserved heterogeneity, we see in columns 1 and 2 that the hazard is downward-sloping for both non-zero investment and investment spikes, in accordance with the nonparametric results discussed above. Tests firmly indicate that we can reject the hypothesis that the entire hazard is flat (test 1). However the significant downward slope is mainly due to the hazard falling sharply in the years immediately after investment; for both non-zero investment and spikes we can reject the hypothesis that the hazard is flat for durations shorter than or equal to four years, and for neither model can we reject the hypothesis the hazard is flat for durations longer than four years (tests 2 and 3). We have also tested wether the slope of the hazard in the initial four years of duration pool over countries, and over size.[43] These tests (tests 4 and 5) indicate that we cannot reject the hypothesis that the slope of the hazard is common over size, and across countries. In this model, as in all the following models, firms with higher profit rates have a significantly higher hazard of investing or having an investment spike. This is consistent with the findings of Bigsten et al. (1999), and squares well with fact that most firms finance investments by internal means. Further, as expected, the hazard of investing is significantly higher for larger firms, while the hazard of having an investment spike is lower for older firms.

Although the above results suggest that duration dependence is negative, it should be kept in mind that the results may be biased due to the omission of unobserved heterogeneity. In columns 3 and 4 we report NPML results of the discrete random effects model for non-zero investment, and spikes, respectively. We found that three support points were sufficient

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[42]Including dummies for the year that the spell began (to capture cohort effects), as in CHP, would bias the hazard estimates, due to the particular way that the firms were sampled. Specifically, since we construct the duration variable by looking back in time and count the number of years since the most recent investment occurred, a spell with an early start date is bound to be a long spell. Therefore, such year dummies would pick up duration effects, and the hazard would be biased. See Data Appendix for details on sampling and construction of variables.

[43]Specifically, we interacted the duration dummies d2-d4 with the log of employment, and the country dummies, respectively, and tested for the joint significance of the interaction terms.

for the non-zero investment hazard, and that two points were sufficient for the spike hazard.[44] In each model, one mass point is normalized to zero due to the inclusion of an intercept. The discrete random effects, or mass points coefficients, are denoted e_j, where j indexes the mass point, and their associated estimated probabilities are denoted Prob(e_j).

It is evident from these results that the inclusion of unmeasured heterogeneity through nonparametric random effects affects the results quite substantially. Most importantly, for both non-zero investments and spikes, the point estimates of the duration coefficients now indicate that the hazard of investment is higher 2-5 years after most recent investment than in the year immediately after investment. For non-zero investment (column 3) the duration coefficients are imprecisely estimated, and the hypothesis that the hazard is flat cannot be rejected at conventional levels, neither can the hypothesis that the hazard for durations 2-4 years is higher than that of one year (tests 1 and 2, respectively). Further, the improvement in the log-likelihood value obtained in column 2 is not large enough to render the model without unobserved heterogeneity too restrictive.[45] However, for the spike hazard, the duration coefficients on d2-d6 are all individually significant at less than 10 percent, and the hypothesis that the coefficients on d2-d4 are jointly zero can be rejected at 10 percent level of significance (test 2). As usual in hazard models, the hazard coefficients of longer durations are less precisely estimated, which explains why the hypothesis that the entire hazard is flat cannot be rejected (test 1).

As for the effects of the regressors (other than sector and country dummies), firm size and the profit rate remain positive and significant in the non-zero hazard, while their point estimates are slightly different compared to the ML estimates. In the spike model, only the profit rate is significant, and highly so. For both non-zero and spike investments, the baseline hazard in the initial four years of inactivity pools over size and across countries, as indicated by tests 4 and 5, respectively.

We now turn to the estimation of panel logit models. Since tests of the logistic baseline hazard in Table 9 indicated that we cannot reject the hypothesis that the hazard is flat for durations longer than three years, we choose a lag length of three periods (i.e. J=3, in equation (10) above). The first lag of the dependent variable, and two duration dummies are included, which means that the following transition probabilities can be estimated:

Prob[y(it)=1 | y(i,t-1)=1, x(it)];
Prob[y(it)=1 | y(i,t-1)=0, y(i,t-2)=1, x(it)];
Prob[y(it)=1 | y(i,t-1)=0, y(i,t-2)=0, y(i,t-3)=1, x(it)]; and
Prob[y(it)=1 | y(i,t-1)=0, y(i,t-2)=0, y(i,t-3)=0, x(it)].

---

[44]Adding more support points led to minor or no improvements in the log likelihood value.

[45]The associated LR statistic is 2.63, which is too small to reject the null with four additional parameters.

This particular lag structure implies that the there exist four different conditions:

$$y_{i0}^{S} = \begin{cases} w_1 \ \ if \ y_{i0} = 1 \\ w_2 \ \ if \ y_{i0} = 0, \ d_{2i0} = 1 \\ w_3 \ \ if \ y_{i0} = 0, \ d_{2i0} = 0, \ d_{3i0} = 1 \\ w_4 \ \ if \ y_{i0} = 0, \ d_{2i0} = 0, \ d_{3i0} = 0 \ . \end{cases}$$

Hence, based on (5'), the full likelihood we will maximize can be written

$$L_i \times (p_{w1})^{1[y_{i0}^{S}=w_1]} (p_{w2})^{1[y_{i0}^{S}=w_2]} (p_{w3})^{1[y_{i0}^{S}=w_3]} (p_{w4})^{1[y_{i0}^{S}=w_4]},$$

where $p_{w1},..., p_{w4}$ are the probabilities (summing to unity) associated with each of the initial conditions, and $1[a]$ are indicator functions being equal to 1 if the event a is true and zero otherwise.

$$L_i = \sum_{m=1}^{M} \prod_{t=S}^{T} H_{it}(e_m)^{y_{it}} [1 - H_{it}(e_m)]^{(1-y_{it})} Pr(\eta_i = e_m | y_{i0}^{S} = w),$$

The results, reported in Table 10, indicate that the coefficients on the lagged dependent variables are consistent with a downward sloping hazard: the likelihood that a firm makes an investment (or a spike) is highest if the previous investment (spike) occurred recently, and then declines as the time of inactivity increases. Focussing on the non-zero investment model, we see that allowing for unobserved heterogeneity is also important in this framework, since the heterogeneity term e_2 is highly significant. Moreover, it is important to acknowledge that the initial conditions are endogenous. The conditional probabilities that the random effect is equal to the estimated mass point, e_2, vary with the particular initial lag structure. This casts some doubt on the hazard results above. As for the effect of the lags, controlling for unobserved heterogeneity makes a difference: without such controls, the estimated coefficients (and hence the transition probabilities) are monotonically falling, but this is not the case when unmeasured heterogeneity is taken into account. This can be seen more clearly in Table 11, where we report predicted transition probabilities implied by the four specifications in Table 10. In fact, the negative duration dependence becomes less pronounced when controlling for this kind of heterogeneity. This is to be expected, for reasons discussed above. However, the effect is not strong enough to yield positive duration dependence. Tests (not reported) indicate that we can reject the hypothesis that lag coefficients are jointly zero. As for the effect of exogenous variables, age is negatively related to the propensity to invest, whereas employment, profits and the change in employment are positively related to this decision.

Turning finally to the results of the spike model, these are qualitatively similar to those of the investment propensity model: duration dependence is negative, the age coefficient is negative, and the coefficients on employment, profits and the change in employment are positive. However, one important difference is that no significant unobserved heterogeneity is found, since the e_2 coefficient is insignificant (also log likelihood values are similar). We tried parametric forms as well (i.e. assuming the random effects to be normally distributed), but this did not alter the results.

VI. Conclusions

We have examined dynamic patterns of capital adjustment in five sub-Saharan African countries, assessing the consistency of those patterns with different adjustment cost structures. Similar to the findings for a number of other countries, our results are mixed.

In the descriptive analysis, we have documented the importance of zero investment episodes and lumpy investment at the firm level. The average investment rate of firms highest ranked investment is almost three times higher than that of the second highest, and represents half of total investment. This pattern of zeros and lumps seems decisively at odds with models based on quadratic adjustment costs. The fact that a significant portion of firm investments are small is not inconsistent with fixed costs, if we assume that adjustment costs for replacement investment are not important, and fixed costs are only relevant for expansion investment. In addition, the proportion of firms experiencing large investment spikes is significant in explaining aggregate manufacturing investment.

Next, we examined the predictions from two particular models of adjustment costs. First, consistent with the CE model, we found average investment in Cameroon, Kenya, Zimbabwe and possibly Ghana, was a convex function of the difference between desired and actual capital. On average, firms adjusted proportionally more to large disequilibria than to small. The non-responsiveness of investment to small disequilibria is also consistent with irreversibilities.

Second, we used various transition data models to examine the shape of the hazard function: the hazard of investing, or having an investment spike as a function of the time since the last investment or spike. The nonparametric sample hazard and logistic hazard models yielded a downward-sloping hazard function. This is consistent with quadratic costs and with piecewise linear costs (irreversibilities) in the CHP model. When we control for unobserved heterogeneity in the logistic hazards, however, the hazards are upward sloping for both the non-zero investment model and the investment spike model. An upward-sloping hazard is consistent with fixed costs in the CHP model. There are qualifications to these results, however. First, we cannot reject the hypothesis that the hazard is actually flat from the fourth duration (or years since the last investment) onward. Second, we are not able to confirm these results when we utilize dynamic panel logits, a different econometric methodology. Following from the finding of a flat hazard for long durations in the logistic hazard, here we only look at effectively three durations. For both the non-zero investment and investment spike model we found negative duration dependence, which is equivalent to a

Table 1. Investment Propensities, by Country and Firm Size

Employment	Cameroon	Ghana	Kenya	Zimbabwe	Zambia	Total
1<= <=5	0.205 78	0.312 80	0.439 180	0.529 51	0.288 132	0.355 521
5< <=20	0.294 143	0.437 167	0.399 193	0.508 122	0.294 177	0.382 802
20< <=100	0.238 147	0.477 153	0.407 280	0.627 177	0.281 228	0.403 985
>100	0.377 146	0.196 363	0.439 264	0.709 543	0.376 189	0.464 1505
Total	0.288 514	0.317 763	0.421 917	0.655 893	0.31 726	0.416 3813

Note: Top numbers in each cell are pooled proportions of positive investments during one year. Bottom numbers are numbers of observations. The table is based on data from the full sample of 821 firms.

Table 2. Proportion of Firms Selling Equipment

	Any Disinvestment			Disinvestment rate >10%		
	Small (L<=20)	Large (L>20)	All	Small (L<=20)	Large (L>20)	All
Cameroon	0.067 60	0.132 53	0.097 113	0.0 60	0.0 53	0.0 113
Ghana	0.043 70	0.075 67	0.058 137	0.014 70	0.03 67	0.022 137
Kenya	0.048 83	0.146 96	0.101 179	0.0 83	0.031 96	0.017 179
Zimbabwe	0.146 41	0.361 122	0.307 163	0.049 41	0.008 122	0.018 163
Zambia	0.068 59	0.115 61	0.092 120	0.0 59	0.016 61	0.008 120
All	0.067 313	0.193 399	0.138 712	0.01 313	0.018 399	0.014 712

Note: Top numbers in each cell are proportions of firms ever experiencing the relevant capital sales event during the survey periods. Bottom numbers are numbers of firms. Due to incomplete observations, calculations are based on data on 712 of the 821 firms in the full sample.

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Note: Top numbers in each cell are proportions of firms ever experiencing the relevant capital sales event during the survey periods. Bottom numbers are numbers of firms. Due to incomplete observations, calculations are based on data on 712 of the 821 firms in the full sample.

Table 3. Distribution of Investment Rates and Contribution to Aggregate, by Country

Investment Rate (I/K)	Cameroon	Ghana	Kenya	Zimbabwe	Zambia	All
0	0	0	0	0	0	0
	--	--	--	--	--	--
0<<.05	0.297	0.12	0.219	0.162	0.19	0.174
	0.27	0.409	0.402	0.356	0.458	0.381
.05<=<.1	0.278	0.091	0.226	0.118	0.058	0.13
	0.155	0.157	0.202	0.217	0.151	0.189
.1<<=.2	0.165	0.425	0.158	0.24	0.213	0.235
	0.189	0.157	0.161	0.166	0.12	0.159
.2<<=.3	0.086	0.153	0.11	0.134	0.057	0.126
	0.115	0.091	0.06	0.07	0.076	0.076
.3<<=.4	0.013	0.12	0.052	0.089	0.028	0.079
	0.041	0.054	0.039	0.072	0.022	0.051
.4<	0.161	0.09	0.235	0.256	0.454	0.256
	0.23	0.132	0.137	0.12	0.173	0.144
N	514	763	917	893	726	3813

Note: Top numbers are shares of aggregate investment contributed by each category, where aggregate investment is the total investment expenditure over time in each country sub-sample (and pooled for the column "All"). Bottom numbers are proportions of total non-zero observations in each sub-sample. The table is based on data from the full sample of 821 firms.

Table 4. Distribution of Investment Rates and Contribution to Aggregate, by Size

Investment Rate (I/K)	Employment<=20	Employment>20
0	0	0
	--	--
0<<.05	0.060	0.175
	0.336	0.402
.05<=<.1	0.086	0.130
	0.175	0.195
.1<<=.2	0.123	0.236
	0.171	0.153
.2<<=.3	0.094	0.126
	0.094	0.068
.3<<=.4	0.057	0.079
	0.051	0.051
.4<	0.580	0.254
	0.173	0.131
N	1323	2490

Note: See Table 3. Data have been converted to real 1991 USD.

Table 5. Ranked Investment Rates, Persistence, and Contribution to Aggregate

Rank		Ghana	Kenya	Zimbabwe	Zambia	All
	Mean (I/K)	0.269	0.273	0.316	0.308	0.292
1 (High)	Adjacent (I/K)	0.040	0.056	0.093	0.035	0.062
	Share of Total	0.495	0.448	0.488	0.799	0.499
	Mean (I/K)	0.078	0.117	0.151	0.085	0.115
2	Adjacent (I/K)	0.100	0.094	0.146	0.091	0.113
	Share of Total	0.333	0.288	0.249	0.150	0.251
	Mean (I/K)	0.010	0.048	0.070	0.020	0.043
3	Adjacent (I/K)	0.097	0.110	0.114	0.087	0.105
	Share of Total	0.170	0.175	0.112	0.043	0.115
	Mean (I/K)	0.002	0.019	0.031	0.005	0.017
4	Adjacent (I/K)	0.074	0.094	0.104	0.102	0.094
	Share of Total	0.002	0.055	0.096	0.005	0.085
	Mean (I/K)	0.000	0.006	0.014	0.001	0.007
5 (Low)	Adjacent (I/K)	0.058	0.100	0.132	0.108	0.103
	Share of Total	0.000	0.034	0.056	0.004	0.050
	Number of Firms	97	123	147	69	436

Note:
1. Only firms with at least five observations on investments, and who invested at least once, were included. The Cameroonian sub-sample has too few firms with sufficient information to compute statistics of the type reported in the table, and therefore we confine attention to the other four countries in this particular case. See Section A3.2 in the data appendix.
2. Mean (I/K) are average investment rates across firms for each given rank; Adjacent (I/K) are average investment rates in the year(s) after and/or before the rank; Share of Total are shares contributed to aggregate investment by each rank, where aggregate investment has been calculated as explained in the note below Table 2.

Table 6. Regression of Aggregate Investment on Highest Rank Proportions
Dependent Variable: Log [Aggregate Investment/Aggregate Capital]

Variable	
Intercept	-4.28
	(8.05)**
Prop. Highest Rank	4.745
	(1.90)#
Adj. R-squared	0.120
Number of observations	20

Note: Estimation method is OLS. Absolute t-values in parenthesis. Significance at 1 percent and 10 percent is indicated by ** and #, respectively. Prop. Highest Rank is the proportion of firms having their highest rank in a given year.

Table 7. Average Hazard Regressions Dependent Variable: Investment Rate (I/K)

Variable	Cameroon	Ghana	Kenya	Zimbabwe	Zambia
Intercept	0.058	0.052	0.045	0.088	0.037
	(0.010)	(0.010)	(0.007)	(0.007)	(0.010)
Capital Imbalance	0.097	0.012	0.048	0.168	0.008
	(0.022)	(0.020)	(0.016)	(0.016)	(0.017)
(Capital Imbalance)^2	0.059	0.090	0.106	0.148	0.036
	(0.041)	(0.034)	(0.028)	(0.028)	(0.030)
F-test	9.8	3.89	10.8	66.5	0.75
Adj. R-squared	0.05	0.02	0.03	0.18	0.00
N	114	152	189	183	148
NT	375	358	601	587	323

Note:
1. Estimation method is OLS, and standard errors are in parenthesis. It is strictly not appropriate to base inference on these standard errors because zero observations in the dependent variable are included, and because the imbalance variable is a generated regressor. Hence, the regression results should primarily be interpreted as descriptive statistics.
2. For sample issues, see Section A3.3 in the data appendix.

Table 8. Pooled Non-parametric Sample Hazard Estimates

Duration Between Two Events (in Years)	Event: Investment>0		Event: Spike, (I/K)>.10	
	Hazard	Std. Error	Hazard	Std. Error
0	0.42	0.02	0.2	0.02
1	0.24	0.03	0.12	0.02
2	0.21	0.03	0.09	0.02
3	0.13	0.03	0.07	0.02
4	0.12	0.04	0.05	0.03
5	0.07	0.03	0.05	0.03
6	0.02	0.02	0.03	0.03
7	0.12	0.05	0.06	0.04
8	0.14	0.08	--	--
Log-rank Pooling Test* (Prob.)	$\chi(9)=5.69$ (0.77)		$\chi(9)=7.25$ (0.61)	
Number of Firms	682		427	
Prop. Right Censored	0.32		0.63	

Note: The hazard is estimated as $\lambda(j)=d(j)/n(j)$, where d(j) is the number of firms investing after j years, and n(j) is the number of firms in the "risk set". Standard errors are computed as $s(j)=\lambda(j)/[d(j)^{0.5}]$.
* This tests the null hypothesis that hazard functions are equal across the country-size groups defined in Figures 5 and 6, respectively. See Kalbfleisch and Prentice (1980), pp. 17-18, for details about the test procedure.

Table 9. Logistic Hazard Results (Continued)

	ML Estimates (No unobserved heterogeneity)		NPML Estimates (Nonparametric random Effects)	
	(1) Investment>0	(2) Spike: (I/K)>.10	(3) Investment>0	(4) Spike: (I/K)>.10
Intercept	-1.838	-2.145	-2.734	-5.131
	(0.261)**	(0.362)**	(1.249)*	(0.842)**
d_2	-0.637	-0.575	0.106	0.948
	(0.155)**	(0.226)*	(0.51)	(0.473)*
d_3	-0.713	-0.783	0.371	1.392
	(0.191)**	(0.283)**	(0.736)	(0.583)*
d_4	-1.162	-0.955	0.107	1.65
	(0.275)**	(0.376)*	(0.888)	(0.670)*
d_5	-1.214	-1.289	0.201	1.303
	(0.341)**	(0.536)*	(0.99)	(0.774)#
d_6	-1.794	-1.141	-0.270	1.464
	(0.482)**	(0.618)#	(1.121)	(0.856)#
d_7	-3.138	-1.820	-1.590	1.186
	(1.022)**	(1.030)#	(1.451)	(1.208)
d_8	-1.196	-0.971	0.488	2.030
	(0.503)*	(0.756)	(1.213)	(0.984)*
d_9	-0.746		1.082	
	(0.643)		(1.411)	
Ghana	1.226	0.786	2.185	0.965
	(0.217)**	(0.321)*	(0.839)**	(0.578)#
Kenya	0.893	0.508	1.616	-0.008
	(0.196)**	(0.292)#	(0.637)*	(0.568)
Zimbabwe	2.13	1.401	3.541	2.655
	(0.222)**	(0.301)**	(1.055)**	(0.536)**
Zambia	0.942	-0.104	1.681	-2.743
	(0.224)**	(0.386)	(0.660)*	(0.840)**
Wood	-0.1	-0.226	-0.227	0.006
	(0.181)	(0.264)	(0.332)	(0.426)
Textile	-0.514	-0.371	-0.896	-1.106
	(0.176)**	(0.25)	(0.408)*	(0.451)*
Metal	-0.025	-0.185	-0.130	-0.926
	(0.172)	(0.257)	(0.314)	(0.499)#
Log Employment	0.104	0.078	0.195	0.054
	(0.045)*	(0.065)	(0.104)#	(0.113)
Age/100	0.426	-1.327	0.509	-0.320
	(0.525)	(0.805)#	(0.909)	(1.251)
Profit/Capital	0.077	0.160	0.122	0.334
	(0.033)*	(0.042)**	(0.058)*	(0.067)**
Δ Employment	0.231	0.228	0.266	0.246
	(0.148)	(0.213)	(0.191)	(0.326)

	ML Estimates (No unobserved heterogeneity)		NPML Estimates (Nonparametric random Effects)	
	(1) Investment>0	(2) Spike: (I/K)>.10	(3) Investment>0	(4) Spike: (I/K)>.10
e_2			3.398 (1.145)**	5.997 (0.734)**
e_3			-2.147 (0.799)**	
Pr(Intercept)			0.478 (0.127)**	0.737 (0.029)**
Pr(e_2)			0.165 (0.121)	0.263 (0.029)**
Pr(e_3)			0.357 (0.149)*	
Log L	-835.09	-423.92	-833.77	-418.79
χ^2-test (1)	$\chi^2(8)=60.46$ $Pr>\chi^2=0.00$	$\chi^2(7)=21.99$ $Pr>\chi^2=0.00$	$\chi^2(8)=6.90$ $Pr>\chi^2=0.55$	$\chi^2(7)=7.67$ $Pr>\chi^2=0.36$
χ^2-test (2)	$\chi^2(3)=35.55$ $Pr>\chi^2=0.00$	$\chi^2(3)=14.73$ $Pr>\chi^2=0.00$	$\chi^2(3)=1.11$ $Pr>\chi^2=0.78$	$\chi^2(3)=6.98$ $Pr>\chi^2=0.07$
χ^2-test (3)	$\chi^2(5)=5.50$ $Pr>\chi^2=0.36$	$\chi^2(4)=0.84$ $Pr>\chi^2=0.93$		
χ^2-test (4)	$\chi^2(12)=6.97$ $Pr>\chi^2=0.86$	$\chi^2(11)=8.39$ $Pr>\chi^2=0.68$	$\chi^2(12)=7.31$ $Pr>\chi^2=0.84$	$\chi^2(11)=7.99$ $Pr>\chi^2=0.71$
χ^2-test (5	$\chi^2(3)=6.25$ $Pr>\chi^2=0.10$	$\chi^2(3)=2.33$ $Pr>\chi^2=0.51$	$\chi^2(3)=6.23$ $Pr>\chi^2=0.10$	$\chi^2(3)=2.58$ $Pr>\chi^2=0.46$

Note:

1. Excluded dummy category is a Cameroonian firm in the food sector. Note: Standard errors, reported in ( ), were computed from the inverse of the Hessian. Significance at 1 percent, 5 percent, and 10 percent is indicated by **, *, and #, respectively.
2. NPML is short for Nonparametric Maximum Likelihood.

χ^2-test (1) is a Wald test of H_0: Duration dummy coefficients are jointly zero (i.e. hazard is flat).
χ^2-test (2) is a Wald test of H_0: Coefficients on d2, d3, and d4 are jointly zero (i.e. flat segment of hazard).
χ^2-test (3) is a Wald test of H_0: Coefficients on d4, d5,...,d8 (max d7 for spikes) are equal (i.e. flat segment of hazard).
χ^2-test (4) is a Wald test of H_0: Coefficients on interaction terms between country dummies and d2, d3, and d4, are jointly zero.
χ^2-test (5) is a Wald test of H_0: Coefficients on interaction terms between log employment and d2, d3, and d4, are jointly zero.

Table 10. Dynamic Panel Logit Results, Lag Structure is Three Periods

	ML Estimates (No unobserved heterogeneity)		NPML Estimates (Nonparametric random effects)	
	Investment>0	Spike: (I/K)>0.10	Investment>0	Spike: (I/K)>0.10
IDUM(t-1)	1.549	1.266	1.089	1.155
	(0.141)**	(0.16)**	(0.191)**	(0.314)**
d_2	0.520	0.413	0.513	0.377
	(0.186)**	(0.231)#	(0.207)*	(0.281)
d_3	0.498	0.182	0.596	0.030
	(0.231)*	(0.313)	(0.251)*	(0.348)
Food	0.144	0.138	0.204	0.13
	(0.156)	(0.192)	(0.178)	(0.2)
Wood	-0.071	-0.106	-0.008	-0.121
	(0.161)	(0.204)	(0.184)	(0.237)
Textile	-0.365	-0.351	-0.463	-0.367
	(0.153)*	(0.198)#	(0.184)*	(0.207)#
Ghana	1.316	1.082	1.696	1.163
	(0.256)**	(0.333)**	(0.328)**	(0.37)**
Kenya	0.998	0.648	1.199	0.676
	(0.234)**	(0.315)*	(0.301)**	(0.335)*
Zimbabwe	1.635	1.359	1.914	1.44
	(0.246)**	(0.314)**	(0.318)**	(0.341)**
Zambia	0.579	-0.005	0.668	0.043
	(0.248)*	(0.363)	(0.317)*	(0.384)
Age	-0.01	-0.025	-0.010	-0.026
	(0.005)*	(0.006)**	(0.005)#	(0.007)**
log Employment	0.225	0.123	0.252	0.128
	(0.042)**	(0.051)**	(0.049)**	(0.055)*
Profit Rate	0.047	0.147	0.053	0.146
	(0.025)#	(0.027)**	(0.027)#	(0.028)**
ΔEmployment	0.429	0.520	0.473	0.514
	(0.129)**	(0.164)**	(0.139)**	(0.168)**
Year 1992	0.090	0.344	0.219	0.356
	(0.254)	(0.335)	(0.268)	(0.336)
Year 1993	0.377	0.594	0.541	0.609
	(0.255)	(0.33)#	(0.27)*	(0.332)#
Year 1994	0.226	0.674	0.326	0.696
	(0.283)	(0.363)#	(0.299)	(0.366)#
Year 1995	0.622	0.686	0.802	0.663
	(0.407)	(0.555)	(0.454)#	(0.567)
Intercept	-2.718	-3.322	-3.275	-3.386
	(0.366)**	(0.481)**	(0.474)**	(0.517)**
e_2			2.569	1.758
			(0.644)**	(3.048)
$\Pr(\eta_i=e_2 \mid y_{i0}^S=w_1)$			0.325	0.058
			(0.096)**	(0.266)
$\Pr(\eta_i=e_2 \mid y_{i0}^S=w_2)$			0.000	0.000
			(0.001)	(0.000)
$\Pr(\eta_i=e_2 \mid y_{i0}^S=w_3)$			0.000	0.164
			(0.000)	(0.415)
$\Pr(\eta_i=e_2 \mid y_{i0}^S=w_4)$			0.038	0.000
			(0.045)	(0.001)
P_{w1}	0.465	0.258	0.465	0.258
	(0.017)**	(0.016)**	(0.017)**	(0.016)**
P_{w2}	0.122	0.079	0.122	0.079
	(0.011)**	(0.010)**	(0.011)**	(0.010)**
P_{w3}	0.055	0.045	0.055	0.045
	(0.008)**	(0.007)**	(0.008)**	(0.007)**
P_{w4}	0.358	0.618	0.358	0.618
	(0.017)**	(0.017)**	(0.017)**	(0.017)**
log L	-1909.9	-1453.8	-1901	-1452.8

Note:

1. Excluded dummy category is a Cameroonian firm in the metal sector in 1991. Standard errors, reported in ( ), were computed from the inverse of the Hessian for all models. Significance at 1 percent, 5 percent, and 10 percent is indicated by **, *, and #, respective.

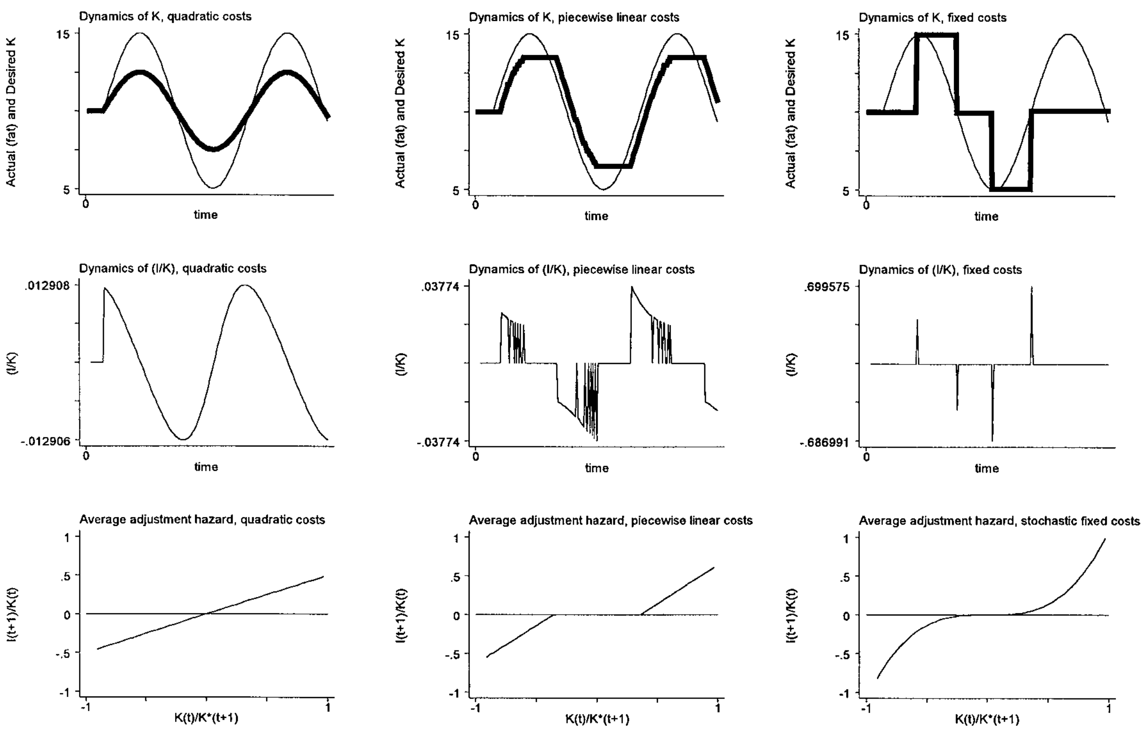
2. Note: Since there are only two support points (where e_1 is normalized to zero, since there is an intercept), the terms Pr(Intercept | w) are equal to 1-Pr(e_2 | w) and the associated standard errors are the same as for Pr(e | w).

Table 11. Predicted Transition Probabilities Implied by Results in Table 9

	Investment>0			Spike: (I/K)>0.10		
	No RE	RE=0	RE=e_2	No RE	RE=0	RE=e_2
Prob(1|1)	0.66	0.53	0.94	0.32	0.29	0.7
Prob(1|0,1)	0.41	0.39	0.89	0.16	0.16	0.52
Prob(1|0,0,1)	0.41	0.41	0.9	0.14	0.12	0.43
Prob(1|0,0,0)	0.29	0.27	0.83	0.12	0.11	0.43

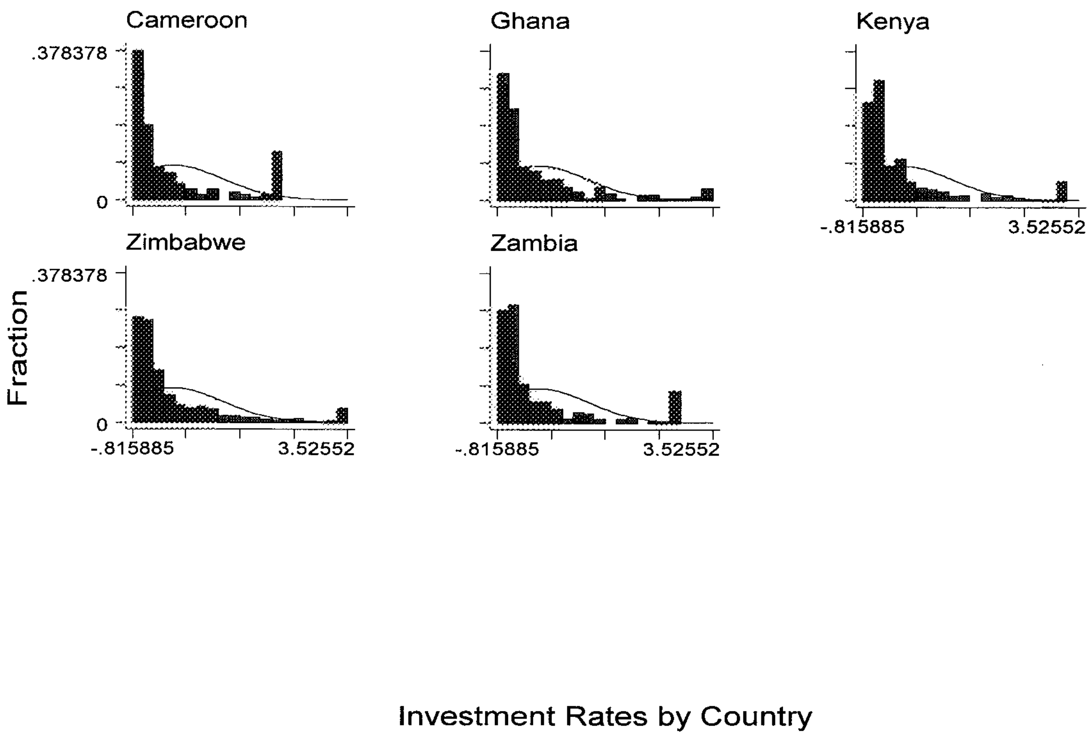
Note: RE is short for Random Effects. Transition probabilities are evaluated at mean values of regressors.

Figure 1. Adjustment Costs and Investment Patterns



Note: In top row, the thin line depicts the path of the capital stock under no adjustment costs, and the thick line shows the path under three different adjustment cost structures (see Hamermesh and Pfann, 1996). The middle row deducts the associated actual investments, approximated as log K_t - log K_{t-1}. The bottom row is from Goolsbee and Gross (1997), and shows the average investment response to imbalances in the capital stock.

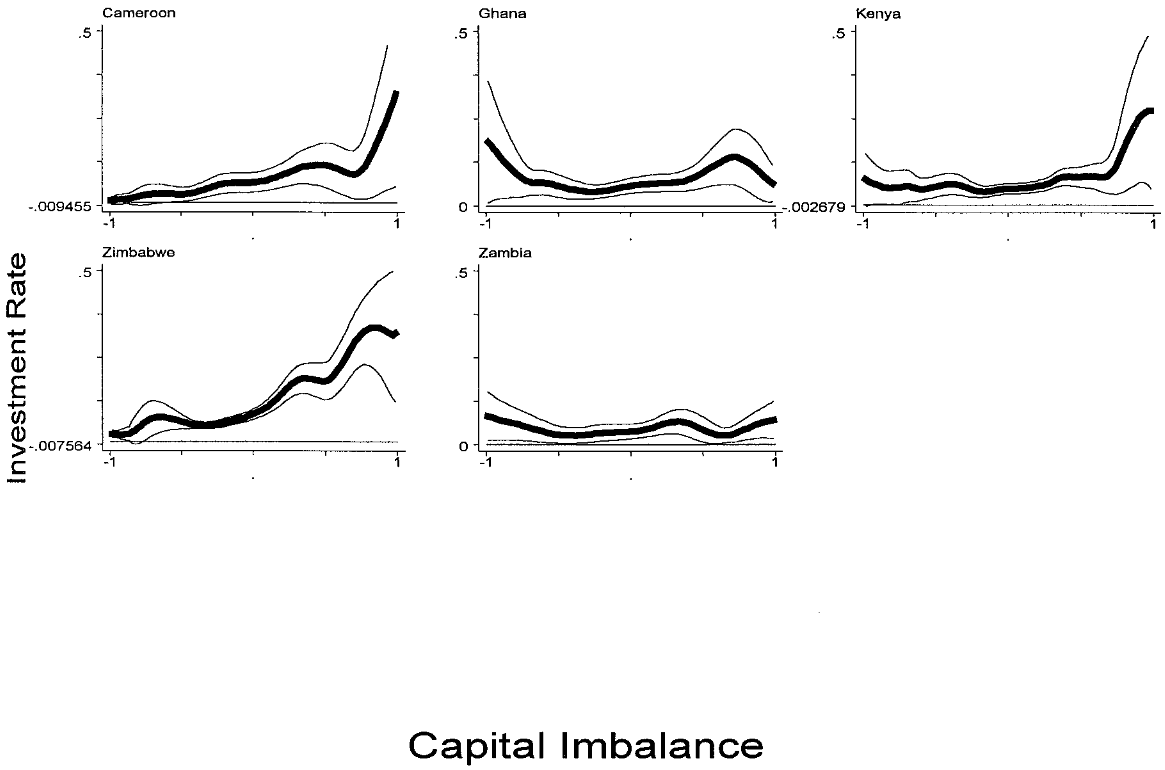
Figure 2. Standardized Investment Rates for Investing Firms, by Country



Note: Investment rates are standardized by subtracting the sample average and dividing the resulting variable by the sample standard deviation.

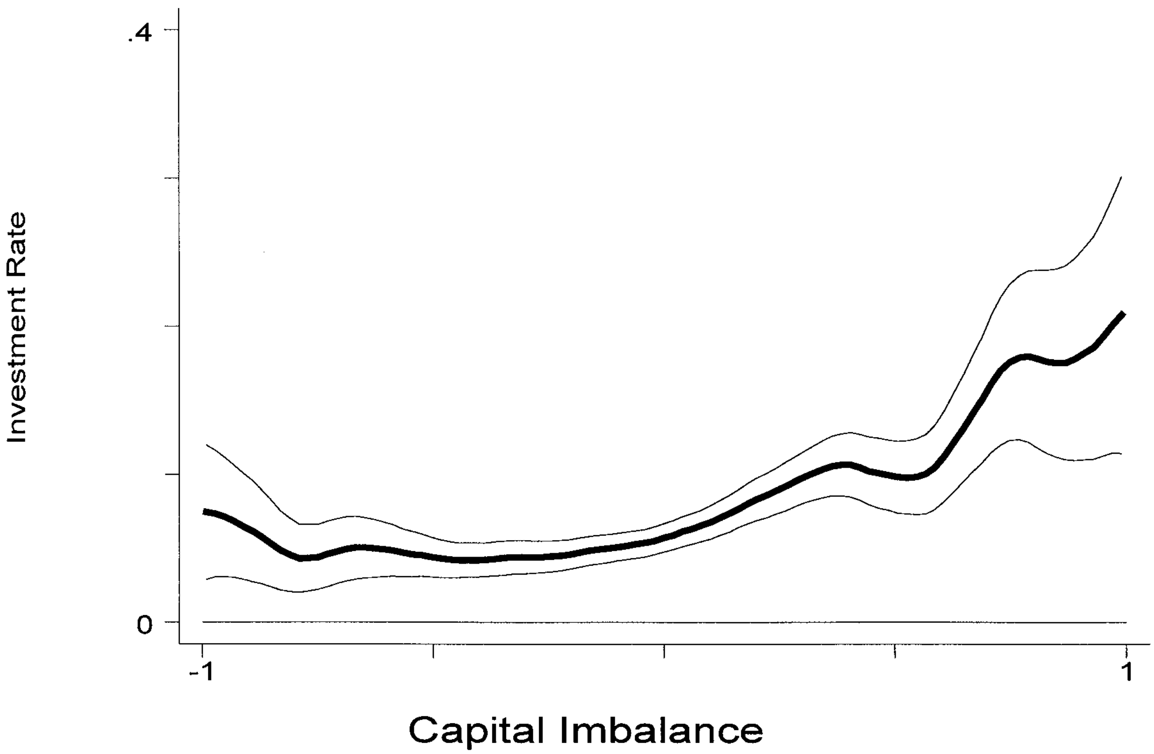
Figure 3. Nadaraya-Watson Nonparametric Average Hazard Regressions, by Country

Model: $(I/K)=f\,[\,(I/K)^{MANDATED}\,] + error$



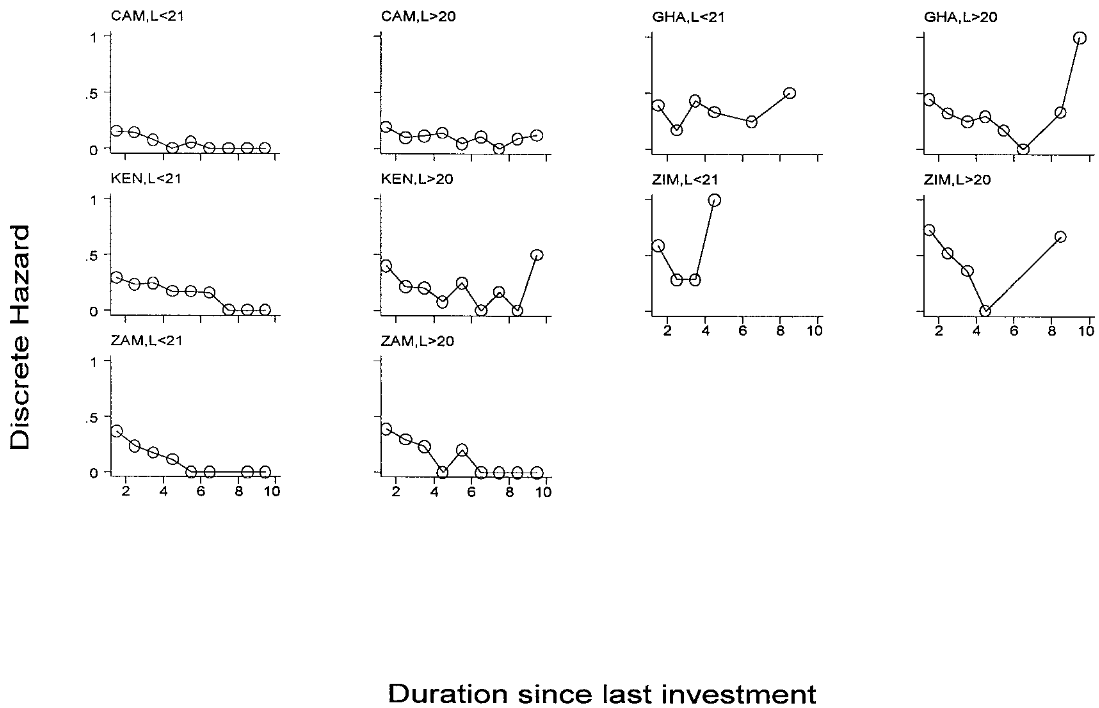
Note: The kernel is triangular, and bandwidth numbers are calculated according to the formula h=2.347*σ*$n^{(-.2)}$ (see Goolsbee and Gross, 1997, and Silverman, 1986), where σ is the standard deviation of the independent variable and n is the number of observations. This gives h=.298 for Cameroon, h=.294 for Ghana, h=.238 for Kenya, h=.238 for Zimbabwe, and h=.327 for Zambia. The results are not sensitive to the choice of kernel. The thin lines indicate pointwise confidence intervals with 95% confidence level, calculated using the XploRe (see http://www.xplore-stat.de/) macro "regci".

Figure 4. Nadaraya-Watson Nonparametric Average Hazard Regression, Pooled
Model: $(I/K)=f[(I/K)^{MANDATED}] + \text{error}$



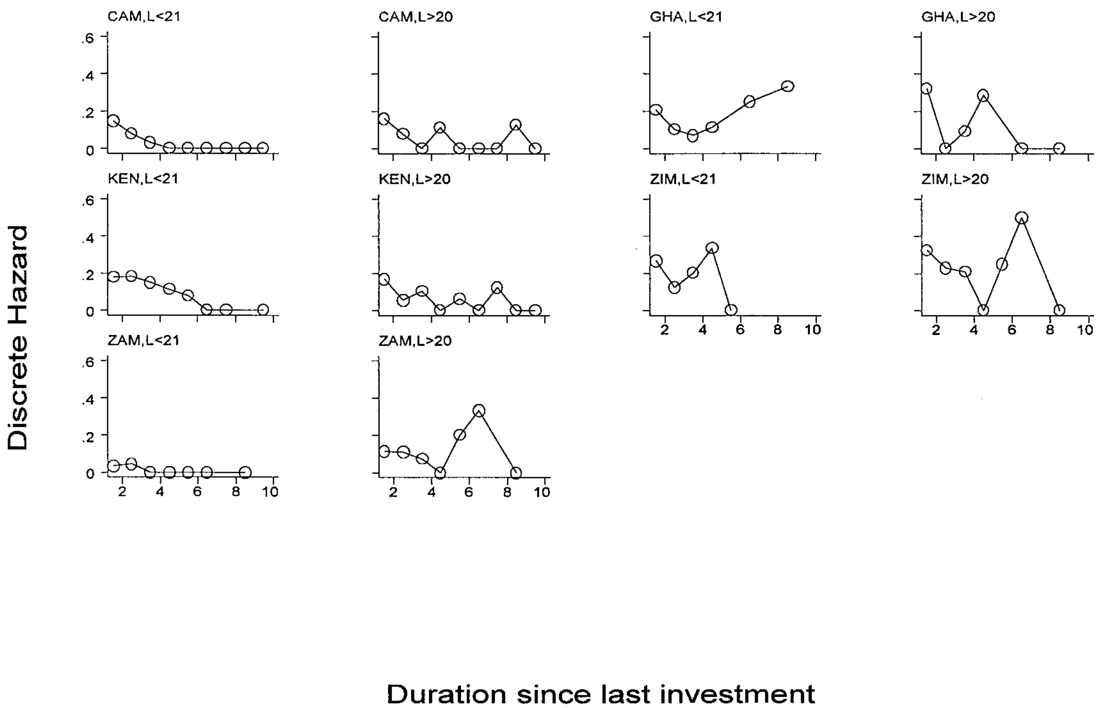
Note: The kernel is triangular, and bandwidth numbers are calculated according to the formula $h=2.347*\sigma*n^{(-.2)}$ (see Goolsbee and Gross, 1997, and Silverman, 1986), where σ is the standard deviation of the independent variable and n is the number of observations. This gives $h=.198$. The results are not sensitive to the choice of kernel. The thin lines indicate pointwise confidence intervals with 95 percent confidence level, calculated using the XploRe macro "regci".

Figure 5. Estimated Sample Hazard Functions, by Country and Size
Event terminating spell: Investment>0



Note: L denotes employment.

Figure 6. Estimated Sample Hazard Functions, by Country and Size
Event terminating spell: Investment Spike, (I/K)>.10



Definition of Variables

Investment: Investment expenditure is defined as the expenditure on equipment and machinery. In each of the three survey rounds, information was obtained about investment in the previous year. Further, in the first year, retrospective information on investment was obtained either by the question "What is the date [year] of the most recent acquisition of equipment?" (Cameroon, Kenya, Zambia, and Zimbabwe), or by extracting information about investment during each of a fixed number of pre-sample years (Ghana). With the exception of Cameroon, in subsequent survey rounds retrospective information on investment stretching back two years or more before the first survey was obtained.

The investment rate, (*I/K*), is defined as investment divided by the replacement value of capital (see below for the latter).

Replacement value of capital: Reported values from the question on replacement value of equipment were used. Missing values could sometimes be replaced by values calculated from a perpetual inventory formula, see below.

Employment: First, the number of employees at the time of survey was used, and second, when the first source was missing and for years prior to the sampling period, retrospective information was used. For the Cameroonian sub-sample, there exist retrospective information about employment in 1982, 1987, and 1992; for Ghana, there exist data on employment in 1983 and 1988; for Kenya, 1981, 1986, 1990, and 1991; for Zimbabwe, 1981, 1986, 1991, and 1992; and for Zambia, 1981 1986, 1990, and 1991. In addition, there is information about employment at the time of start-up of the firm, which in some cases makes it additionally possible to fill in holes in the series.

Output: In each of the three survey rounds, information was obtained about output, defined as the output value at current market prices, in the previous year. Whenever output data were missing we used retrospective data: for Cameroon we used output data for 1992; for Kenya, we used data on the value of sales in 1990 and 1991; and for Zimbabwe we used the value of sales in 1991. The only set of results that are partially based on these retrospective data are the average hazard regressions in Table 7.

Profit: Profit is calculated by subtracting the cost of raw materials, total indirect costs, and wages from the output value. Output is defined as under (iv) above. Indirect costs involve costs for rent, electricity, water, telephone, liquid and solid fuel, and transportation. Wages does not include allowances; when missing, it was replaced by wages including allowances.

Since there exist no retrospective data on either of cost of raw materials, indirect costs, or wages, the profit variable can only be obtained for the years within the sampling period.

The profit rate is defined as profit divided by the replacement value of capital.

Age: Age is defined as current year minus start-up year of firm, plus one.

Sub-samples used in the Analysis: The basis for the analysis is the full sample of 821 firms. However, some parts of the analysis require a structure of the data not fulfilled by all firms in the full sample, and these parts hence have to be based on fewer firms.

Investment propensities and investment rates: Tables 2, 3, and 4 are based on the full sample of 821 firms. In addition to contemporaneous data from the three survey years, we use data from two years before the first survey year. Thus, each firm has at least three observations and at most five observations, and the period covered is in effect 1989-1995.

Investment ranking: For the calculations in Tables 4 and 5 we discard firms with less than five observations on investment and firms which make no investment during the five-year period. These rules reduce the sample to 464 firms, distributed across countries as follows: Cameroon, 28; Ghana, 97; Kenya, 123; Zimbabwe, 147; and Zambia, 69. Since the Cameroonian sample is so small, we confine attention to the other four countries, who thus make up a sample of 436 firms together, as reported in Table 4.

Average hazard analysis: The first step involves estimating the parameters of the first-order condition for the long-run desired capital stock, given that the underlying technology is Cobb-Douglas. The calculations require data on output and investment, and we use all retrospective information on output that is available. This means that we use one pre-sample year for Cameroon and Zimbabwe, two for Kenya, and none for Ghana and Zambia. Further, we delete observations for which the output to capital ratio is in the top or bottom 3 percentiles.The fixed effects estimates are shown in Table A1. We estimate the first-order conditions freely, rather than imposing the theoretical restriction that the coefficient on (log of) output should equal one.

Table A1. First Step Fixed Effects Estimates
Dependent Variable: ln Capital

Variable	Cameroon	Ghana	Kenya	Zimbabwe	Zambia
ln Output	0.442 (0.053)**	0.125 (0.078)	0.093 (0.041)*	0.275 (0.057)**	0.133 (0.062)*
F(N-1,NT-N-1)	F=11.3 Pr>F=0.00	F=9.0 Pr>F=0.00	F=12.6 Pr>F=0.00	F=10.2 Pr>F=0.00	F=5.6 Pr>F=0.00
R-squared (overall)	0.79	0.69	0.76	0.86	0.69
N*T	407	416	732	624	89
N	116	160	196	185	160

Note: Significance at 1 percent and 5 percent is indicated by ** and *, respectively. Standard errors in ( ). The null hypothesis of the F-test is that all firm dummy coefficients are equal (i.e. no fixed effects).

The predicted values from these regressions can be interpreted as desired long run capital plus a constant. Defining mandated investment as the deviation between desired capital and lagged actual capital, we proceed to the second step where we regress actual investment on mandated investment. Since the nonparametric estimator we use (see Figures 3 and 4) is quite sensitive to outliers, we exclude observations for which mandated investment is in the top or bottom 5 percentiles. Moreover, since the model requires a lag of actual capital, we lose one further observation per firm unless retrospective information on the capital stock is available.

Duration regressions: We use all available contemporaneous and retrospective information on investment, and construct durations of investment (or spike) inactivity by counting the number of years between any two investment episodes. We index each duration for every firm, and pick the first duration for each firm (single spell analysis). We right censor durations longer than nine years at nine, and discard left censored durations (i.e. durations for which the start year are unknown). The latter means that the number of firms will be smaller than the full sample number of 821.

In the logistic hazards we model durations as a function of explanatory variables. Since the durations often stretch back into pre-sample years, there are insufficient data on profits to use the annual profit rate as an explanatory variable. Therefore, we use the within duration average profit rate for each firm. For the rest of the explanatory variables, we use annual values defined above..

Panel logit regressions: In order to construct the dependent binary variable and its associated lags, as described in Section 4.3.2, we use retrospective information on investment. Data on exogenous variables are obtained from the three survey years only, thus the panel is unbalanced with at least one and at most three observations per firm. For the non-zero investment model, the full sample of 821 firms was used, whereas for the spike model 795 firms were included. Those lost in the latter case were again due to left censoring.

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