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Which Firms Invest Less Under Uncertainty? Evidence from Ethiopian Manufacturing

Admasu Shiferaw

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Wilhelm-Weber-Str. 2 · 37073 Goettingen · Germany
Phone: +49-(0)551-3914066 · Fax: +49-(0)551-3914059

Email: crc-peg@uni-goettingen.de Web: http://www.uni-goettingen.de/crc-peg

Which Firms Invest Less Under Uncertainty?

Evidence from Ethiopian Manufacturing

*Admasu Shiferaw**

College of William and Mary
Economics Department
Williamsburg, VA 23187
Email: ashiferaw@wm.edu

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Abstract

The paper analyses firms' investment response and the degree of caution they exercise during uncertainty. Using panel data from Ethiopian manufacturing, the investment-uncertainty relationship is examined across groups of firms with varying degrees of irreversibility and scale of production. The paper finds a nonlinear investment response to the "investment-gap" mainly among large firms. Uncertainty reduces the average investment rate particularly in industries where capital is highly irreversible. The trajectory of aggregate investment is also driven by the distribution of lumpy investment at the micro level.

JEL: D21, D81, O16

Keywords: Investment, Uncertainty, Irreversibility, African Manufacturing, Ethiopia.

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1. Introduction

Investment remains an enduring source of economic growth especially in the developing world where it is also a major conduit for technology transfer. As a forward-looking decision, investment involves a careful assessment of the uncertainty surrounding payoffs. Major advances have been made over the last few decades in the theory of investment under uncertainty essentially by relaxing the assumptions on capital adjustment costs, on market structures and on the formation of expectations. While more nuanced than their neoclassical predecessors, the recent theoretical models do not concur on the sign of the investment-uncertainty relationship. Models based on irreversible investment predict that uncertainty undermines the firm's investment response while models that assume convex marginal revenue product of capital in some stochastic variables predict a non-negative effect of uncertainty.

Most of the existing evidence on this issue comes from industry or macro level studies which are ill suited to test the implications of the recent theoretical models of investment (Leahy and Whited, 1996). Since the 1990s, however, a handful of firm level studies emerged from developed countries showing the undesirable effects of uncertainty on investment (Leahy and Whited, 1996; Guiso and Parigi, 1999; Bloom et al., 2007). Similar studies on developing country firms are very rare (Gelos and Isgut, 2001a, 2001b; Bigsten et al, 2005) and almost all of them examine the nature of adjustment costs and the timing of lumpy-investment episodes rather than assessing directly the investment-uncertainty relationship. Little is known, therefore, about the role of uncertainty on the investment behavior of firms in the developing world although their business conditions are presumably much less predictable than in advanced economies. The popular support for policies aimed at economic stability to promote investment seems to be driven as much by commonsense as it is by systematic empirical evidence.

This paper contributes to this discussion by providing a firm level analysis of the investment-uncertainty relationship in a large Sub-Saharan African country. The analysis starts with the assumption that capital stock is hardly at its desired level inasmuch as adjustment costs are nontrivial and that firms invest/disinvest in response to idiosyncratic shocks to the desired stock of capital. A key variable in this analysis is the deviation of capital stock from its desired level, which we refer to as 'mandated investment' following Caballero, Engel and Haltiwanger (1995). The paper estimates mandated investment in a first step and examines the firm-level investment response to changes in the investment-gap using both non-parametric and parametric approaches. The objective is to estimate the degree of caution that firms exercise in responding to the investment-gap under uncertainty and irreversibility. Finally, the paper examines if shocks to the distribution of firm-level investment influence aggregate investment dynamics.

While the current investment literature focuses essentially on demand uncertainty, there are reasons to suspect that uncertainty in the supply of critical inputs, such as electricity, could play a comparable if not a greater influence on investment in developing countries. Business networks and physical infrastructure in many developing countries are not sufficiently developed to allow seamless production processes even when returns to investment are fairly predictable. Dollar et al. (2005), for instance, show that the quality of infrastructural services plays a significant role on productivity growth, investment and returns to factor inputs in a sample of firms from Bangladesh, China, India and Pakistan. In this paper we also reach beyond demand uncertainty and takes into account the role of supply side uncertainty.

The main empirical strategy is to exploit firm heterogeneity in investment under uncertainty as implied by existing theoretical models. One dimension of heterogeneity is the degree of irreversibility of investment projects which will be captured through product market structure and the presence of secondary market for capital goods. The paper also investigates variation in the investment response across the firm size spectrum given the overwhelming evidence that small and large firms differ widely in terms of access to finance, choice of production technology and export orientation. For instance, Whited (2006) finds evidence that small firms with financial constraints are less likely to have episodes of lumpy investment. Using this strategy and a Generalized Method of Moments (GMM) estimation technique, we find a statistically significant decline in firm level investment rate with the uncertainty of demand for manufactured goods and the risk of electricity blackouts. Firm size matters a lot and it is only larger firms who respond systematically to changes in both the investment-gap and uncertainty. The uncertainty effect is pronounced in those industries where capital is hard to reverse. Finally, the firm level distribution of lumpy investment is a critical driver of aggregate investment.

The paper is organized in eight sections. The next section highlights the relevant literature on investment under uncertainty. Section 3 describes the data and the measurement of key variables. Section 4 presents a non-parametric analysis of actual and mandated investment by firm size. Section 5 outlines the econometric model and the estimation method, the results of which are presented in section 6. Section 7 discusses the implications of firm level investment decisions on aggregate investment dynamics. Conclusions and some policy implications are discussed in section 8.

2. Theory and empirics of investment

The inadequacy of investment models with convex and symmetric adjustment costs to explain actual investment has prompted a new generation of investment models under uncertainty. Alternative specifications of adjustment costs, market structure and production technologies paint different pictures about the investment-uncertainty nexus. One class of models recognizes that capital is at least partly irreversible because of asymmetric adjustment costs, i.e., disinvestment being more costly than positive investment. This implies that firms with irreversible investment plans have strong incentive to assess carefully their future cash flows in order to avoid getting stuck with excess capacity. Dixit and Pindyck (1994) show that uncertainty about future payoffs creates an "option value" of waiting for more information that would help firms dispel the uncertainty. The option value of waiting becomes part of the opportunity cost of investment driving a wedge between the marginal revenue product of capital and its user cost. Most importantly, the option value of waiting increases with the degree of uncertainty and extends the range of investment inaction.

However, other investment models predict a non-negative effect of uncertainty. Hartman (1972) and Abel (1983) show that under perfect competition and constant returns to scale, the marginal revenue product of capital is convex in product prices. A mean-preserving increase in the variance of demand would thus lead to an increase, rather than a decrease, in investment as firms prefer to hold reserve capacity[1]. According to Caballero (1991), however, the Hartman-Abel result does not hold if the underlying assumptions are abandoned. He argues that adjustment costs become more asymmetric and investment more irreversible as competition in product markets becomes increasingly imperfect. Accordingly, firms in less competitive markets would be more cautious to invest in the face of uncertainty relative to firms with high price elasticity of demand (competitive markets). For the latter, current investment does not necessarily jeopardize future cash flows. What emerges from these theoretical models is that the role of uncertainty on firm level investment is far from certain and depends on a combination of firm and industry characteristics.

The hitherto widely used investment models based on convex adjustment costs such as the q-model and the Euler-equation, predict firm level investment to be smooth and continuous as firms try to avoid mounting adjustment costs. However, models with non-convex adjustment costs predict intermittent investment due to a range of inaction over which firms neither invest nor disinvest. This has been supported by stylized facts from micro level studies showing that plant level investment is not only discontinuous but also lumpy (Doms and Dunne, 1998). In a theoretical model with stochastic fixed adjustment costs, Caballero and Engle (1999) show a non-linear investment response to the gap between desired and actual stocks of capital following periods of zero investment. Intermittent investment could therefore result from irreversibility, non-convex adjustment costs as well as from other factors such as financial constraints and indivisibility of capital. Disentangling the forces behind intermittent and lumpy capital adjustments has thus been the focus of recent theoretical and empirical studies of investment behavior.

The sign of the investment-uncertainty relationship should also be investigated empirically as it cannot be determined on theoretical grounds alone. Two alternative approaches have been followed in the literature. One approach measures directly the effect of uncertainty on the

[1] This relationship shown in Abel (1983) applies if investment is reversible so that the option value of investing is zero. Pindyck (1988) also shows that the value of an extra unit of capacity increases with uncertainty but so also the option value of waiting which in the end leads to a negative relationship between investment and uncertainty.

[2] Even in the presence of irreversibility, the effect of uncertainty on investment becomes ambiguous if one takes into account the volatility of capital prices in addition to the option value of waiting (Abel, Dixit, Eberly and

average investment rate. Typically a proxy for demand uncertainty would be included in an econometric model of investment often in interaction with product demand. A negative coefficient on the uncertainty proxy and/or its interaction with demand points to the undesirable effect on investment. A major challenge in this approach is the measurement of unobservable idiosyncratic uncertainty.

The other approach tests the investment-uncertainty nexus indirectly by comparing the theoretical and actual adjustment paths of capital. The non-parametric version of this approach plots the actual investment rate against desired (mandated) investment (Goolsbee and Gross, 1997; Gelos and Isgut, 2001b; Bigsten et al., 2005). A range of inaction in this diagram would suggest that adjustment costs are asymmetric and investment is irreversible. Showing that investment is irreversible indeed goes halfway to demonstrating the negative effect of uncertainty.[2] Non-linearity in this adjustment path implies that non-convex adjustment costs could be driving the investment response rather than irreversibility.

The parametric version of the indirect approach involves estimating the probability of a large investment outlay (an investment spike) conditional on a number of factors including the time since the last investment spike (Cooper, Haltiwanger and Power, 1999; Gelos and Isgut, 2001a; Bigsten et al., 2005). A positive duration dependence suggests fixed adjustment costs while a negative duration dependence supports the presence of irreversibility and adjustment cost asymmetry. The basis for such interpretations is the expectation that a firm facing fixed adjustment costs is more likely to replace its capital with the passage of time since its previous episode of lumpy investment. However, if irreversibility is much more binding, capital replacement becomes increasingly less likely in the time elapsed since the last episode of lumpy investment. As already said, studies that follow this approach do not test the role of uncertainty directly and it is difficult to pin down the policy implications.

While theoretical models of investment under uncertainty are inherently microeconomic, most empirical studies are carried out at the industry or macroeconomic level. Carruth, Dickerson

[2] Even in the presence of irreversibility, the effect of uncertainty on investment becomes ambiguous if one takes into account the volatility of capital prices in addition to the option value of waiting (Abel, Dixit, Eberly and Pindyke, 1996).

and Henley (2001) provide a recent review of such studies. Most aggregate level studies that directly include a proxy for uncertainty in an investment equation find a statistically significant negative coefficient. For a sample of 84 developing countries, of which 40 are in Sub Saharan Africa, Serven (1998) finds a statistically significant negative effect of macroeconomic volatility on investment. Similar results were reported by Hadjimichael and Ghura (1995) for a sample of 32 African countries. Nonetheless, the suitability of these studies to test the implication of the theoretical investment models remains doubtful.[3]

Firm level analysis of investment is therefore much more relevant than aggregate level studies to understanding the role of uncertainty. Using a panel of US manufacturing firms, Leahy and Whited (1996) show that uncertainty, proxied by the volatility of stock market prices, has a statistically significant negative effect on investment.[4] Guiso and Parigi (1999) exploit firm heterogeneity in irreversibility on the sign of the investment-uncertainty relationship for a sample of Italian manufacturing firms. Measuring uncertainty by the distribution of managers' expectation of demand growth, they find a negative effect of uncertainty on investment which was stronger for firms with greater irreversibility. [5]

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[3] To begin with aggregate level studies follow the representative firm approach, ignoring firm heterogeneity in the investment-uncertainty relationship which is underscored by the theoretical models they set out to test. Macro-level studies also suffer from the endogeneity problem arising from the effect of aggregate investment on the proxy for demand uncertainty, i.e., the volatility of GDP or stock market prices. Finally, idiosyncratic demand shocks tend to cancel each other out during aggregation, a process which also eliminates the zero investment episodes that characterize models with irreversible investment.

[4] While the use of a GMM estimator allowed the authors to account for firm fixed effects, there are serious doubts on whether the volatility of share prices captures speculation and irrational behavior rather than uncertainty in economic fundamentals. Leahy and Whited (1996) also did not show if the undesirable effects of uncertainty varies across firms depending on the degree of irreversibility.

[5] The authors capture irreversibility by splitting the sample based on the perceived ease of selling equipment in a secondhand market and a measure of market power using observed profit margins. While this is an innovative approach to investigate firm heterogeneity, their econometric models do not control for firm and time fixed effects that could alter their findings.

Evidence from the developing world on the investment-uncertainty relationship is rather sparse. The existing studies follow the indirect approach and examine the relative importance of irreversibility and fixed adjustment costs on the pattern and timing of investment. Gelos and Isgut (2001b) run a nonparametric regression of average investment rate using Mexican and Colombian firm level data and while Gelos and Isgut (2001a) use the same datasets to estimate a duration model for the likelihood of an investment spike. The evidence from both papers is more consistent with irreversibility rather than with non-convex adjustment costs. Similarly, Bigsten et al. (2005) examine the investment patterns of manufacturing firms in five Sub-Saharan African countries using duration models and nonparametric regression[6]. They find negative duration dependence for both the likelihood of non-zero and lumpy investment episodes in Africa which is consistent with irreversibility of capital. While these studies reveal the investment patterns, they are silent on the exact investment-uncertainty relationship for firms in Africa and Latin America.[7]

This paper contributes to this literature by investigating empirically the investment response to mandated investment and how this response is conditioned by uncertainty and irreversibility. The analysis is based on a panel data of Ethiopian manufacturing firms with a more complete industry and firm size distribution than the datasets used in other firm level studies from Sub-Saharan Africa. The econometric analysis is in line with Leahy and Whited (1996), Guiso and Parigi (1999) and Bloom et al. (2007). Similar to Leahy and Whited (1996) and Bloom et al. (2007) the paper uses dynamic panel data estimation while it exploits firm heterogeneity in the investment response under uncertainty as in Guiso and Parigi (1999).

3. The Data and Capital Adjustment Patterns

[6] Bigsten et al. (1999) uses the Euler equation and accelerator models to analyze investment in five Sub-Saharan African countries but did not address uncertainty or irreversibility.

[7] Pattillo (1998) provided the first firm level assessment of investment under uncertainty in Sub-Saharan Africa. Measuring uncertainty based on managers' subjective distribution of expected sales growth, she finds a negative effect of uncertainty for Ghanaian firms whose investment is irreversible. However, the use of cross-sectional data raises serious questions about identification.

The data

This paper uses a panel data of privately owned Ethiopian manufacturing firms over the period 1996 to 2002. The data are collected by the Central Statistical Agency (CSA) of Ethiopia through its annual census of manufacturing which cover all firms with at least 10 workers. The number of private manufacturing firms increased from 448 in 1996 to 694 in 2002 amounting to a total of 4035 firm-years. In calculating the investment rate as a fraction of lagged capital stock as shown below, we lose the observations in 1996. Moreover, due to missing values on investment and exclusion of extreme outliers (observations where net investment is more than 5 times the size of a firm's lagged capital stock) we base our analysis on a total of 2612 firm-years.

The perpetual inventory approach is used to generate the series of actual capital stock taking into account initial book value of capital and subsequent values of investment, capital sales and depreciation:

$$K_{it} = (1-\delta)K_{it-1} + NI_{it}$$
$$NI_{it} = I_{it} - S_{it} \qquad (1)$$

where K_{it} is the capital stock of firm *i* in year *t*, and δ is annual depreciation rate (10% for machinery and vehicles and 5% for structures). NI_{it} is net investment expenditure expressed as the difference between investment expenditure (I_{it}) and capital sold in a secondhand market (S_{it}).

The firm level investment rate is given by $IR_{it} = (I_{it} - S_{it}) / K_{it-1}$ which can be negative depending on the sign of NI_{it}. Net investment rate in excess of 20% is defined as an investment spike or lumpy investment following the practice in the investment literature (Cooper et al. 1999).

In line with Caballero et al. (1995), mandated investment is calculated as the difference between desired and actual capital stock.

$$MI_{it} = \tilde{k}_{it} - k_{it-1} \qquad (2)$$

Where MI_{it} is mandated investment, and $\tilde{k}_{it}$ and k_{it-1} are logarithms of desired and actual capital, respectively. Desired capital is assumed to be a certain proportion of frictionless capital-stock k^*_{it}:

$$\tilde{k}_{it} = k^*_{it} + d_i \qquad (3)$$

where d_i is a plant or industry specific constant. While desired capital refers to the capital stock a firm would hold if there are no adjustment costs during the time of investment, frictionless capital refers to the capital stock one would observe if firms never have to face any adjustment cost. We follow the standard neoclassical approach to arrive at the frictionless capital stock k^*_{it} :

$$k^*_{it} = k_{it-1} + \eta_i \left[\left(y_{it} - k_{it-1} \right) - \theta_i c_{it} \right] \qquad (4)$$

where η_i is the slope of the profit function with respect to capital and y_{it} is the logarithm of output. $\eta_i \approx 1/(1-\alpha_i)$ for a production function with imperfect competition where α_i is computed as the cost share of capital (Caballero et al., 1995). The user cost of capital is computed as:

$$c_{it} = \left. (r_t + \delta_i)\left(PI_t / p_{it} \right) \middle/ (1-\tau) \right. \qquad (5)$$

where r is the real lending rate , δ_i is the depreciation rate, PI_t is the price index of capital goods, p_{it} is firm specific output price index and τ is the business profit tax rate. The firm specific output price index p_{it} is constructed based on the price of the main product of each firm and using 1996 as the base year. This price index is also used to deflate sales. In the absence of industry specific capital goods prices, PI_t was proxied by the unit price index of machinery imports based on annual data from the Ethiopian Customs Authority (ECA) on US Dollar value and volume of machinery imports.[8]

[8] We are assuming here that the composition and technological content of machinery imports to Ethiopia remain stable during the sample period and that industry specific differences in capital prices are negligible.

Once the user cost of capital is calculated, θ_i is estimated from a regression of the natural logarithm of capital-to-output ratio on the user cost of capital. θ_i is the coefficient on c_{it} and it is interpreted as the long-run elasticity of capital with respect to the user cost. This regression is carried out for each industry and the coefficients are found to be negative and statistically significant with a mean value of -0.6, which is slightly less than the neoclassical average of -1. We believe that this is a plausible value since in the African context it is often the lack of access to finance rather than its cost that seems to constrain investment. Figure 1 shows the distribution of θ_i across two digit industrial sectors and over time for the entire manufacturing sector. Finally, desired capital is estimated by adding a constant d_i to frictionless capital. Following the lead from Caballero et al. (1995), d_i is the industry mean gap between desired and actual capital stock and represents the firm level investment that would be needed to keep pace with depreciation.

Since mandated investment proxies the unobserved investment gap based on observed variables as discussed above, several robustness checks have been carried out to ensure that it captures investment fundamentals rather than unobserved shocks and measurement errors[9]. Moreover, the econometric method was chosen in such a way that it minimizes the effects of the latter on estimated parameters.

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[9] To check for the main sources of variation in MI, we run OLS regression on a variant of Equation (4), i.e., $k_{it}^{*} = \eta_i y_{it} - (1-\eta_i)k_{it-1} - (\eta_i\theta_i)c_{it}$. The results show that the three variables explain 88% of the total variation in MI of which 75% is accounted for by change in output. The remaining 13% of variation is due to lagged capital stock. Output has been deflated by firm specific prices to deal with idiosyncratic demand shocks and firm level variation in mark-up pricing. Moreover, the general price level was not volatile during the sample period in Ethiopia with inflation rate of about 10% on average. Another series of mandated investment was calculated using a firm specific version of d_i in equation (3) and the results were very similar to the series based on industry level d_i as shown in Figures A1 and A2 in the appendix for standardized MI. To check if the perpetual inventory approach has generated a reliable capital stock series (given the relatively short span of the panel data), the distribution of MI was compared for two sub-periods, i.e., toward the beginning and toward the end of the sample period. Tests could not reject the equality of the respective distributions.

Summary Statistics

Figure 2 shows a leptokurtic distribution of mandated investment (MI_{it}). Most privately owned firms (about 70% of firm-years) have a positive mandated investment indicating capital shortages while the remaining 30% have excess capacity. The excess kurtosis indicates that firms in this sample are more likely than in a normal distribution to have extreme values of MI_{it}.[10]

Table 1 shows the distribution of actual investment rate across industries. Looking at the last row for the entire manufacturing sector, about 60% of observations have zero investment episodes showing widespread investment inaction relative to European and US firms. Furthermore, 22% of firms with positive investments have a less than 10% investment rates, which is essentially the depreciation rate. At the other extreme, about 12.5% of observations show lumpy investment episodes, i.e., IR_{it} greater than 20%. Investment episodes that are large enough to increase the capital stock are thus very infrequent. Disinvestment is also extremely rare suggesting strong irreversibility of installed capacity.[11] The last column of Table 1 shows that a few firms with investment spikes account for about 80% of total investment in manufacturing underscoring the role of lumpy investment for aggregate investment dynamics.

Table 2 shows that the incidence and rate of investment increases with firm size. About two-thirds of small firms (i.e., firms with less than 50 employees) have zero investment episodes which drops to less than one-third among large firms (with at least 50 employees). Lumpy investment on the other hand is more frequent among large firms (24.2%) as compared to small firms (9.5%). Most of the zero investment episodes therefore occur at the lower end of

[10] Compared to the histogram of mandated investment in Caballero et al. (1995) for US manufacturing, Figure 1 seems to show a sizable proportion of firms with very large investment gaps and relatively high standard errors. However, this is mainly due to differences in sample composition and in units of measurement. Caballero et al. (1995) used a balanced panel of very large firms (mean size of 800 workers) while this paper uses an unbalanced panel of both large and small firms which is dominated by the latter. Moreover, Figure 1 reports the actual value of mandated investment while Caballero et al. reported standardized values. Figure A1 in the appendix shows the histogram of standardized mandated investment for better comparison.

[11] Note that the frequency of firms which have sold a capital good in a secondhand market is about 6%.

the firm size distribution while lumpy investment often occurs at the upper end. This could partly be the result of aggregation over plants as large firms are mostly comprised of more than one production units. It could also reflect the relatively limited access to finance that small firms have. In both size categories, lumpy investment episodes account for about 80% of total investment. The fact the investment spikes are more frequent among large firms is consistent with Figure 3 which shows that large firms account for more than 70% of total investment in the manufacturing sector. In the meantime, the average size of large private sector firms has increased steadily from 96 workers in 1996 to 188 in 2001 before declining to 178 in 2002 while the average size of small firms has remained stable at 20 workers.[12]

The regional difference in investment inaction is quite striking. It is very pervasive in the Ethiopian sample even among large firms while it is very rare (often less than 5%) in developed countries (Doms and Dunne, 1998; Bloom et al., 2007).[13] Gourio and Kashyap (2007) report about 35% near-zero investment for Chilean manufacturing establishments. For a sample of five sub-Saharan African countries, Bigsten et al. (2005) report very high incidence of zero investment episodes: about 71% in Cameroon, 69% in Zambia, 68% in Ghana, 58% in Kenya, and 34% in Zimbabwe[14]. In comparison with developed countries,

[12] Shiferaw and Bedi (2009) find that there has been a reallocation of labor from small to large firms in Ethiopian manufacturing which is consistent with the investment pattern in Figure 4. The story seems in line with Bayer's (2006) model and empirical evidence that access to finance, which is relatively better for large firms, has a short term positive effect on investment by increasing the frequency of investment spikes rather than by increasing the desired stock of capital. Similarly, Whited (2006) finds that financially constrained small firms are less likely to have investment spikes.

[13] This is partly because studies from developed countries often use a balanced panel of large firms unlike the unbalanced panel in this paper which comprises mainly of small firms.

[14] Bigsten et al. (2005) also report that out of the 42% of firms with positive investment in the five countries, 27% have investment rates in excess of 20%. This is equivalent to about 11.3% (27% of 42%) of the total number of firms in the full sample - including those firms with zero investment- which is comparable to the 12.5% of firms with lumpy investment in the Ethiopian sample. In a similar study Bigsten et al. (1999) show that the median investment rate has been zero in four African countries. On the other hand, for a group of five African countries, Bigsten et al. (2005) report that among those firms with positive investment, spikes are more likely among small firms. It should be noted however that Bigsten et al. (2005) use survey data that are overrepresented by large firms unlike the census based panel data in this paper which covers all private sector manufacturing firms in Ethiopia that employ at least 10 workers. It is therefore difficult to compare these results with other African countries.

lumpy investment episodes are more frequent and accounts for a much larger percentage of total investment in Sub-Saharan Africa. For the five Sub-Saharan African countries just mentioned, Bigsten et al. (2005) show that firms with lumpy investment account for 47% of total investment which is nearly twice its contribution in the UK and US[15]. Attanasio et al. (2000) find that firms with investment spikes (5.4% of investment observations) account for 24.6% of total investment in the UK manufacturing. Similarly, Doms and Dunne (1998) report that 25% of total investment in US manufacturing is accounted for by firms with lumpy investment. These are telltale signs of investment frictions that tend to be higher in developing countries.

4. Nonparametric Analysis of Investment Response

In this section we use the Nadaraya-Watson kernel regression to estimate firms' investment response to changes in mandated investment (Goolsbee and Gross, 1997). This nonparametric regression imposes no restrictions on the data and plots the weighted average investment rate at different points in the distribution of MI_{it}. In the presence of non-trivial fixed adjustment cost, there would be a range of inaction at lower levels of discrepancy between desired and actual capital which will be followed by a burst of investment as firms respond to cumulated capital shortages (Caballero and Engel, 1999). This phenomenon will reveal itself in a nonlinear investment response outside the inaction range. If irreversibility is the main concern, the relationship between actual and mandated investment will be linear outside the range of inaction (Hamermesh and Pfann, 1996).

[15] The substantially larger role of lumpy investment in the Ethiopian sample (about 80%) as compared to the average for other SSA countries in Bigsten et al. (2005) has to do with differences in sample composition. The Ethiopian data is based on a manufacturing census that covers all firms that employ at least 10 workers (and hence dominated by small firms) while the RPED data often over-samples large firms. The Ethiopian data in this paper also excludes state owned enterprises which on average are larger than privately owned firms.

Figure 4 shows the Nadaraya-Watson kernel regression with mandated investment on the horizontal axis[16]. It shows clearly a nonlinear investment response to the size of the investment gap as expected from non-convex adjustment costs. Firms experiencing substantial capital shortfall undertake lumpy investment (marked by the third horizontal line) while firms with relatively small investment-gap have an average investment rate of about 10%, tracing closely the second horizontal line at 10%[17]. Firms with small gaps therefore seem to maintain their capital stock by investing just enough to cope with depreciation. However, the picture does not show a range of inaction as the mean investment rate is also positive for manufacturers with excess capital stock. Nonetheless, for firms with excess capacity, the mean investment rate is below the 10% depreciation rate, implying that they allow their capital stock to decline through depreciation rather than through disinvestment. This behavior is consistent with asymmetric adjustment costs and irreversibility of installed capacity.

Figure 5 compares the investment response by firm size. This is important since the industrial landscape of developing countries is heavily dominated by small establishments with limited access to credit, technology and export markets. The difference in the scale of the y-axis reveals that small firms typically invest at a much lower rate than large firms at any point on the distribution of mandated investment. Investment by small firms is also far less sensitive to *MI*, staying close to horizontal line at 10%. For large firms, the investment rate increases steady with *MI*. Unlike small firms, large firms with substantial capital shortages are more likely to have investment spikes. While large and small firms in our sample experience comparable demand shocks, adjustment toward the desired stock of capital is thus evident primarily among large firms, essentially driving the nonlinear investment response documented in Figure 4.

[16] The kernel is Epanechnikov and the confidence intervals are constructed using Xplore www.xplore-stat.de

[17] The widening of the confidence interval also suggests that large changes in desired capital are less frequent and the average investment response to such changes is measured with less precision.

The literature on irreversible investment and non-convex adjustment costs predicts a range of inaction within which firms will neither invest nor disinvest[18]. However, Figures 4 and 5 do not show such a range of inactivity. The fraction of firms with zero investment does not vary much with *MI* particularly for small firms. This is shown in Figure 6 using kernel regression of a dummy variable identifying zero investment episodes on mandated investment. A similar regression using a dummy variable for investment spikes in Figure 7 shows that large firms are more likely than small firms to have lumpy investment episodes. Most importantly, the likelihood of an investment spike tends to rise with mandated investment mainly for large firms. The incidence of lumpy investment among small firms remains around 10% for the most part and only rises above 10% for firms with sizable capital shortfalls.

Summing up, the non-parametric regressions clearly indicate that large firms are more responsive to changes in mandated investment as compared to small firms. Investment by large firms also seems to be more consistent with the adjustment patterns predicted by theories of irreversible investment. While the results in this section are less conclusive about the forces behind the observed patterns of investment, they show that a careful analysis of firm level investment should take into account heterogeneity across firm sizes and the nonlinearity of the investment response.

5. The Econometric Model

Theories of investment with asymmetric and non-convex adjustment costs do not lend themselves to a tractable closed form solution like investment models with convex adjustment costs. Moreover, the alternative market structures assumed by these theories cannot be nested in a single structural model. Given such difficulties, it is not surprising that most econometric applications of these theories focus on their implications on the timing of lumpy investment rather than on the mean investment rate and the sign of the investment-uncertainty relationship. A flexible approach to this problem has been introduced in recent studies using the time series properties of desired and actual capital stock (Bloom et al., 2007; Hall et al., 1999). This approach is based on the recognition that the time series of actual and desired

[18] In Caballero and Engel (1999) the fixed adjustment cost is stochastic and the range of inaction could vary across firms and over time for a firm.

stocks of capital are cointegrated with a stable long-term relationship. Inasmuch as this is the case, there must be a short-term Error Correction Mechanism (ECM) that keeps the two series from wandering away from each other indefinitely. As outlined in section 3, desired capital is defined in a neoclassical fashion as a function of output and the user cost of capital. In this setting, mandated investment is the short-run deviation of actual capital from its desired level and a trigger for investment as a corrective action. Accordingly, Equation 6 shows our basic investment model featuring mandated investment as a covariate. A quadratic term is also included to capture a nonlinear investment response.

$$IR_{it} = \alpha_0 + \alpha_1 MI_{it} + \alpha_2 MI_{it}^2 + v_i + \omega_t + u_{it} \qquad (6)$$

where IR is the investment rate and MI is mandated investment. The firm specific and time fixed effects are represented by v_i & ω_t, respectively, while u_{it} is an equation error term uncorrelated with itself and with other explanatory variables. α_j are parameters to be estimated and, subscripts i and t index firms and years, respectively.

As discussed in sections 3 and 4, firms are more responsive to capital shortages while they tend to tolerate excess capacity. This pattern is consistent with theories of irreversible investment which predict a negative effect of uncertainty. Equation (7) presents a more complete model where demand uncertainty is proxied by the coefficient of variation of firm level output, σ_{it}^D, over a three year moving window. This variable also enters the model in interaction with mandated investment to find out if uncertainty dampens the investment response to demand shocks.

$$\begin{aligned} IR_{it} = {} & \alpha_0 + \alpha_1 MI_{it} + \alpha_2 MI_{it}^2 + \alpha_3 \pi_{it-1} + \alpha_4 \sigma_{it}^D + \\ & \alpha_5 \sigma_{it}^S + \alpha_6 \sigma_{it}^D * MI_{it} + \alpha_7 \sigma_{it}^S * MI_{it} + v_i + \omega_t + u_{it} \end{aligned} \qquad (7)$$

Where π is gross profit rate and, σ^D and σ^S are proxies for demand and supply side uncertainty, respectively. See Table A1 for mean and standard deviation of these variables.

The unreliable supply of key inputs such as electricity and imported intermediate inputs could also lead to volatile cash-flows which in turn undermine investment (Dollar et al. 2005). In equation (7) σ_{it}^{S} represents the unreliable supply of electricity and its influence on investment decisions. However, since power disruptions are exogenous shocks that affect all firms, we attempt to capture the firm specific effect through a measure of the degree of exposure or susceptibility to power failure. We approximate this exposure by the cost of electricity per unit of value added. Since a government agency fixes the price of electricity in Ethiopian, this proxy allows us to capture the degree of reliance of a firm's production process on electricity and hence its exposure to the unpredictable incidences of power failure rather than shocks in electricity prices[19]. Like in the case of demand uncertainty, we interact σ_{it}^{S} with mandated investment to find out if power outages undermine firm level investment directly or through its interaction with change in demand.

If banks tend to decline loan applications by firms with uncertain payoffs, then uncertainty could undermine investment by increasing the chances of being credit rationed rather than or on top of its negative effect on a firm's propensity to invest. Ignoring this transmission mechanism in an investment model could overstate the negative effect of uncertainty (Guiso and Parigi, 1999). In a model with no uncertainty, Bayer (2006, 2008) shows that the frequency of investment spikes increases with the Equity-ratio, a proxy for access to finance, for UK and German firms. In this paper we control for credit rationing by including the gross profit rate in equation (7). The idea is that only credit rationed firms will rely on internal funds for investment; otherwise the so-called Modigliani-Miller condition should prevail where the investment decision is independent of the source of finance[20].

As already indicated earlier, the sign of the investment-uncertainty relationship depends critically on the degree of irreversibility. Like uncertainty, however, irreversibility is unobservable mainly because of the implicit nature of adjustment costs (often expressed as output forgone during adjustment) and partly because firms often do not keep records of even

[19] Dollar et al. (2005) used the percentage of sales foregone due to power failure. While a similar measure in not available in the Ethiopian firm level data, the cross-sectional distribution of sales foregone due to power failure in the Dollar et al. (2005) sample presumably reflects differences in the degree of dependence of each firm's production process on electric power.

[20] Notice that the Euler specification of the investment model predicts a negative coefficient on the cash flow term because the opportunity cost of adjusting the capital stock is higher during periods of high profitability.

observable components of adjustment costs. This paper experiments with two approximations of the degree of irreversibility. The first approach uses the size of the secondary market for capital goods. This can be measured by the fraction of firms in an industry who participated in the secondary market. However, this measure ignores the depth of the secondhand market in terms of the actual volume of transactions. We therefore augment it by the total value of capital traded in the secondhand market normalized by the total capital stock of all firms in a given industry. The product of these two ratios is our proxy for the scope of the secondhand market; a statistic that captures both the extensive and intensive margins of the market:

$$Z_j = \frac{n_j}{N_j} * \frac{\sum_{i=1}^{n} S_{ij}}{\sum_{i=1}^{N} K_{ij}} \qquad (8)$$

where *i* and *j* index firms and industries, respectively, *Z* is the proxy for the scope of the secondhand market, *n* is the number of firms participating in the secondhand market, *N* is the total number of firms in an industry, *S* is the value of capital sold by a firm in the secondhand market, and *K* is the capital stock of a firm.

The larger the value of *Z*, the easier it is to reverse investment decisions. Once this proxy is calculated for each industrial sector, we split the sample into those firms whose *Z* score is above and below the manufacturing sector average. The expectation is that the negative effect of uncertainty on investment should be stronger if it is harder for firms to reverse investment decisions. Moreover, firms with the possibility to reverse their investment decisions should be more responsive to changes in mandated investment.

The second approach of assessing irreversibility is by gauging the product market structure as suggested in Caballero (1991). He argues that the degree of irreversibility varies inversely with the degree of market competition, i.e., it increases as we move from perfectly competitive markets to highly concentrated markets. Accordingly, uncertainty is expected to play a negative role for firms in less competitive markets. We use the Herfindahl Concentration Index to capture market structure in our sample. This index is simply the sum of the squared market shares of all firms in an industry[21]. The larger the value of the index, the less competitive the market is and the more difficult to reverse investment projects. Using this index we split the sample into those industries with a Herfindahl index above and below the median. It is possible that this approach may capture reversibility better than the one based on secondhand markets. The latter may not reflect the true extent of irreversibility if, for instance, selling a capital good entails a sharp discount even when a secondary market exists.

In line with the nonparametric analysis in section 4 which revealed important differences in investment behavior across firm size, the econometric model will also be estimated for large and small firms separately.

Estimation Method

Equation (7) shows the main thrust of the paper, i.e., analyzing the investment response to changes in the investment-gap and uncertainty and the interactions thereof. While this is consistent with investment models with non-convex adjustment costs, in the empirical applications we include the lagged investment rate as a covariate to allow for persistence in investment predicted by models with convex adjustment costs. Since the fixed and random effects panel data estimators are inconsistent in such dynamic settings, we use the Blundel and Bond (1998) system GMM estimator. First differencing of the variables by the GMM estimator removes time invariant unobserved firm specific effects such as innate productivity differences that could influence both the investment-gap and the investment rate. The GMM estimator also allows us to control for aggregate level shocks such as technology induced differences in the pace of capital replacement as well as macroeconomic shocks that shift the desired capital stock across time for the entire manufacturing sector. These aggregate shocks are accounted for by including sector and time dummy variables, respectively.

The Blundell and Bond (1998) system GMM estimator uses suitably lagged levels as instruments for variables in first differences and lagged differences as instruments for

[21] Although the sample excludes state-owned enterprises, the market shares and the Herfindahl index are calculated taking into account both public and private firms.

variables in levels. Provided that they pass the overidentification test, these internal instruments minimize the endogeneity problem that we suspect in some of our covariates. For instance, while a sizable investment in the current year does not enter the production process until next year, small investment outlays for maintenance purposes and minor upgrades could be correlated with current sales and hence with our proxy for demand uncertainty. Similarly, the GMM instruments will minimize the potential correlation of the error in Equation (7) with shocks in mandated investment arising from innovations in firm specific demand and the user-cost of capital.

6. Discussion of results

The results of the GMM estimator are presented in Tables 3 and 4. The model is estimated for the entire sample as well as for sub-samples of small and large firms separately. For each group of firms two specifications are estimated, i.e., with and without interaction terms between mandated investment and the proxies for uncertainty.

The set of instruments easily pass the overidentification test suggesting that they are not correlated with the equation error. This is shown by the Sargan-Hansen statistics reported at the bottom of the results' tables. The Arelano and Bond (1991) test cannot reject the presence of a first order autoregressive process (AR1) in the error term of the first difference equation, which of course is the result of first differencing. The same test rejects an AR2 process except for few cases where both AR1 and AR2 are rejected for large firms. There is thus a measure of confidence in the results from the system GMM estimator.

Table 3 presents the results of the model ignoring differences in irreversibility of investment. Investment by large firms is significantly responsive to changes in mandated investment while that of small firms is not. The fact that only the quadratic term of *MI* is statistically significant suggest that even large firms tend to wait for the investment-gap to grow bigger before making capital adjustments. These results are consistent with the observations from the non-parametric analysis[22]. Table 3 also shows that the two uncertainty proxies have the expected

[22] While lagged investment has a statistically significant coefficient in both sub-samples, the coefficient is positive in the case of small firms and negative in the case of large firms. This finding points to important differences in the investment behavior of small and large firms. A positive coefficient on lagged investment in

negative sign and are statistically significant for the entire sample. When the model is estimated separately for small and large firms, the coefficient on demand uncertainty becomes imprecise although it still is correctly signed. The coefficient on σ^S remains negative and significant for both subsamples indicating that disruption of power supply dampens the investment response.

Most importantly, the interaction of demand uncertainty with *MI* has a statistically significant negative effect for large firms. This suggests that large firms are more cautious in their investment response to the investment-gap at higher levels of uncertainty. Overall, the results of the investment model without accounting for irreversibility reveal a negative effect of uncertainty on investment – an effect measured with more precision among large firms. This is not surprising given the earlier observation that the investment response to *MI* increases with firm size. Large firms are also more susceptible to electricity blackouts as they are more capital intensive than small firms.

Table 4 presents the results of the investment model taking into account firm heterogeneity in irreversibility. This is done by estimating the model separately for firms with and without secondhand markets for capital goods[23]. A key finding is that the ability to reverse investment projects make large firms more proactive in their investment decisions. The coefficient on the quadratic term of mandated investment is positive and significant only for large firms with

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the sub-sample of small firms is consistent with our previous observation that small firms invest mainly for maintenance purposes which presumably entail much less adjustment costs and accordingly minor scrutiny of future cash flows. A negative coefficient on lagged investment in the case of large firms suggests that large firms are more likely to have intermittent and lumpy investment episodes which are then followed by periods of either zero or relatively small investment outlays. This is broadly consistent with the findings of negative duration dependence for the probability of investment spikes in a number of studies (Bigsten et al., 2005).

[23] The sample split by the size of secondhand markets reduces the number of observations on large firms making the number of instruments appear proportionally larger. Although the instruments in Table 4 pass the overidentification test, a further robustness check was made by increasing the number of firms and observations with nonmissing values. The model was estimated again on larger sample sizes of both small and large firms by using different multiple imputation methods to fill missing observations. The results are reported in Table A3 which shows results that are qualitatively very similar to that of Table 4.

secondhand markets while its linear term is significant across all sub-samples. For large firms without secondhand markets, MI^2 has a statistically significant negative coefficient implying that average investment rate increases at a decreasing rate with mandated investment. This finding underscores the critical role of irreversibility on the investment behavior of large firms facing highly volatile demand. Small firms without secondhand markets are not responsive at all to changes in mandated investment. However, small firms with secondhand markets show unexpected behavior in the sense that their investment rate declines with *MI* at an increasing rate.

Another key observation is that the proxies for demand and supply side uncertainties have negative and statistically significant coefficients for large firms without secondhand markets. For large firms with secondhand markets, uncertainty does not undermine investment and in fact demand volatility has a positive and significant coefficient. The interaction of demand uncertainty with *MI* has the expected negative coefficient of similar magnitude for large firms with and without secondhand markets pointing to the cautious investment response under uncertainty. These results are consistent with theories of irreversible investment where uncertainty matters most if investment is hard to reverse.

Table 4 shows that while uncertainty also undermines investment by small firms, its effect does not vary systematically with the degree of irreversibility. It can be said that the investment behavior of large firms is more in line with the theoretical literature on irreversibility and uncertainty as compared to that of small firms.

Market Structure

To check the robustness of results in Table 4, Table 5 presents the regression results of the model in which irreversibility is defined on the basis of product market competitiveness. The table shows that the average investment response to changes in desired investment is stronger for firms operating in competitive markets as compared to those in concentrated markets. This is a result one would expect if capital is indeed harder to reverse in less competitive markets which in turn undermines investment el la Caballero (1991). Large firm in competitive markets have positive and statistically significant coefficients on the linear and quadratic terms of *MI* while for large firms in concentrated markets only the quadratic term is positive and significant. For small firms in competitive markets, the quadratic term of mandated investment is negative and significant while small firms in less competitive markets are not responsive to mandated investment.

The coefficients on the proxies for demand and supply side uncertainty also confirm that uncertainty reduces the investment response mainly in markets with imperfect competition. We also find that the coefficient on the interaction of *MI* with supply side uncertainty is negative and significant for large firms in concentrated markets but positive and significant for large firms in competitive markets – a result which is in agreement with the story that uncertainty is less binding for firms in competitive markets. Summing up the results, the weight of evidence is in favor of a negative relationship between investment and uncertainty which becomes magnified for firms with irreversible investment.

To check the robustness of these results to changes in the dynamic structure of the econometric model in equation (7), the investment model was re-estimated by removing the lagged dependent variable from the model. Table 6 presents the results where irreversibility is proxied by the secondhand market. The results confirm the previous conclusions that large firms are more responsive than small firms to changes in *MI*. The interaction terms with *MI* have the expected negative sign for large firms with irreversible investment. That means firm level investment is lower in the presence of uncertainty if the project is irreversible similar to the results from the dynamic specification[24].

7. Implications on Aggregate Investment

[24] Compared to the results in Tables 4 and 5, the coefficients on demand uncertainty are positive in the non-dynamic specifications in Table 6, while the interaction terms with mandated investment remain negative and significant. This is likely a reflection of the different channel through which shocks to lagged investment are transferred to current investment. Since lagged investment increases current capital stock and output, which in turn perturb the uncertainty proxy, this effect will be picked up by the uncertainty proxy if lagged investment is excluded. For relatively small changes in the uncertainty proxy, this could result in a positive relationship between the uncertainty proxy and current investment if investment episodes tend to be clustered.

This section examines how the micro dynamics of investment influence the trajectory of aggregate investment. The idea is to find out whether shocks to the distribution of firm level investment have aggregate level implications. Caballero (1999) and Caballero et al. (1995) show that the proportion of firms with lumpy investment has a significant effect on aggregate investment in US manufacturing. Gourio and Kashyap (2007) find similar results for Chilean and US firms. However, Thomas (2002) shows a general equilibrium model where firm heterogeneity in investment should not affect aggregate investment dynamics.

Aspects of the distribution of firm level investment that are relevant for the aggregate analysis are the fraction of firms with zero and lumpy investment as well as the mean investment rate of firms with investment spikes. Aggregate investment is calculated as the weighted average investment rate of all firms in a 2-digits SIC industry, using as weights the employment shares of firms in that industry. The model in equation (9) also includes industry fixed effects to account for unobserved variation in production technology and market structure. It also includes time fixed effects to control for shocks in exchange rate, interest rate and other macro variables that could drive aggregate investment across all sectors. The estimation model is:

$$IR_{jt} = \sum_{i=1}^{N} \left({l_{ijt}}/{L_{jt}} \right) \left({I_{ijt}}/{K_{ijt-1}} \right) = \beta_0 + \beta_1 INA_{jt} + \beta_2 SPK_{jt} + \beta_3 SPKR_{jt} + \beta_4 S_j + \beta_5 T + v_{jt} \qquad (9)$$

Where *i, j and t* index firms, sectors and time, respectively. The dependent variable $IR_{Jt} = \sum_{i=1}^{N} \left({l_{ijt}}/{L_{jt}} \right) \left({I_{ijt}}/{K_{ijt-1}} \right)$ is a sector level weighted average of firm level investment rates $\left({I_{ijt}}/{K_{ijt-1}} \right)$ where the weights $\left({l_{ijt}}/{L_{jt}} \right)$ are the employment shares of firms in sector *j*. *INA* is the fraction of firms with investment inaction, *SPK* is the fraction of firms with investment spikes, *SPKR* is the average spike rate, *S* and *T* are respectively sector and time fixed effects, and v_{jt} is a white noise.

OLS estimates of aggregate investment in (9) are reported in Table 8. Columns 1 and 2 show the results without taking into account size specific aspects of the cross-section of investment rate. Columns 3 and 4 present the regression results with the fraction of small and large firms with investment spikes and inaction entering the model separately.

The main observation is that aggregate investment in manufacturing industries increases as the fraction of firms with investment spikes and their average spike rate increase. This pro-cyclical aggregate effect is particularly associated with the investment decisions of large firms. Of primary importance is the percentage of firms with investment spikes than the mean spike rate. This is similar to the finding of Doms and Dunne (1998) that the number of plants going through spikes tracks aggregate investment closely than the average size of the spikes.

However, a regime shift from zero to positive investment does not have significant bearings on the dynamics of aggregate investment regardless of the fact that most firms in our sample have zero investment episodes. This has to do with the fact that most non-zero investment episodes involve small adjustments of capital. The results in Table 8 therefore suggest that in asmuch as uncertainty undermines firms' investment response to business fundamentals, it also stifles aggregate investment mainly by reducing the frequency of lumpy investment.

As indicated in sections 3 and 4, investment spikes are more frequent among large firms. Although a detailed threshold analysis is not the main thrust of this paper, results of a panel logit model reported in Table A2 confirm that the likelihood of an investment spike is higher among large firms and increases with the size of the investment gap up to a certain upper threshold. Although statistically insignificant, spikes are also less likely to occur with the passage of time since the previous incidence of lumpy investment, a pattern expected to prevail in the presence of uncertainty.

8. Conclusions

The paper analyses the role of uncertainty on firm level investment in the manufacturing sector of a large Sub-Saharan African country. It considers uncertainty in product demand and supply of a critical input and, identifies their effect on investment by exploiting firm heterogeneity in scale of production and irreversibility of capital. Despite the prevalence of zero investment episodes, the investment behavior of firms in our sample is broadly similar to observations from other developed and emerging economies. While excess capacity is tolerated due perhaps to irreversibility, there is a nonlinear investment response to large capital shortfalls. The response rate is particularly robust among large firms and weaker among small firms. Moreover, only the investment patterns of large firms seem to be systematically consistent with theoretical models of investment under uncertainty and partial irreversibility. It is possible that small business startups constitute part of capital owners' response to uncertain business environment. Our findings corroborate the observation that most firms in developing countries are born small and remain small (Tybout, 2000), which could be problematic for industrial expansion given the ubiquitous presence of small firms.[25]

The econometric analysis reveals a negative relationship between investment and uncertainty particularly among large firms. Most importantly, the undesirable effect of uncertainty is accentuated in industries where irreversibility is high. Alternative measures of irreversibility provide similar results. Moreover, large firms with a possibility to reverse investment decisions tend to respond vigorously to mandated investment other things being equal. Firm level investment also responds negatively to the unpredictable supply of critical inputs such as electricity. Improving the investment climate through reliable infrastructural services allows firms to achieve quickly their desired stock of capital.

The finding that less competitive industries are susceptible to the undesirable effects of uncertainty requires further research on market structure. If the latter is due to constraints on small firms that in turn leave the entrenched large firms unchallenged, then policy support for small firms could lead to a win-win situation. It could improves investment by reducing irreversibility, while raising simultaneously aggregate productivity through a more competitive environment.

[25] Using the same dataset as in this paper, Shiferaw (2009) shows that multi-unit firms are more likely to survive than single unit firms even after controlling for firm size which suggests that business expansion through branching out is a viable survival strategy that does not necessarily lead to fast growth in aggregate output and productivity. It is therefore not surprising that we did not find small firms to be as responsive to changes in mandated investment as large firms.

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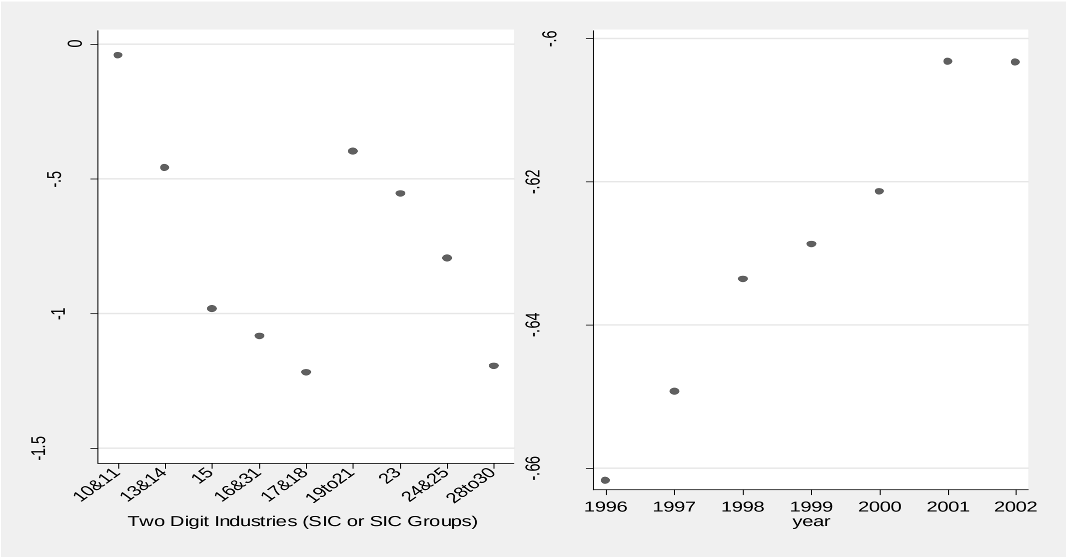

Figure 1: Average Values of the Long Run Elasticity of Capital With Respect of the User Cost (θ), Distribution across-industries and over time.

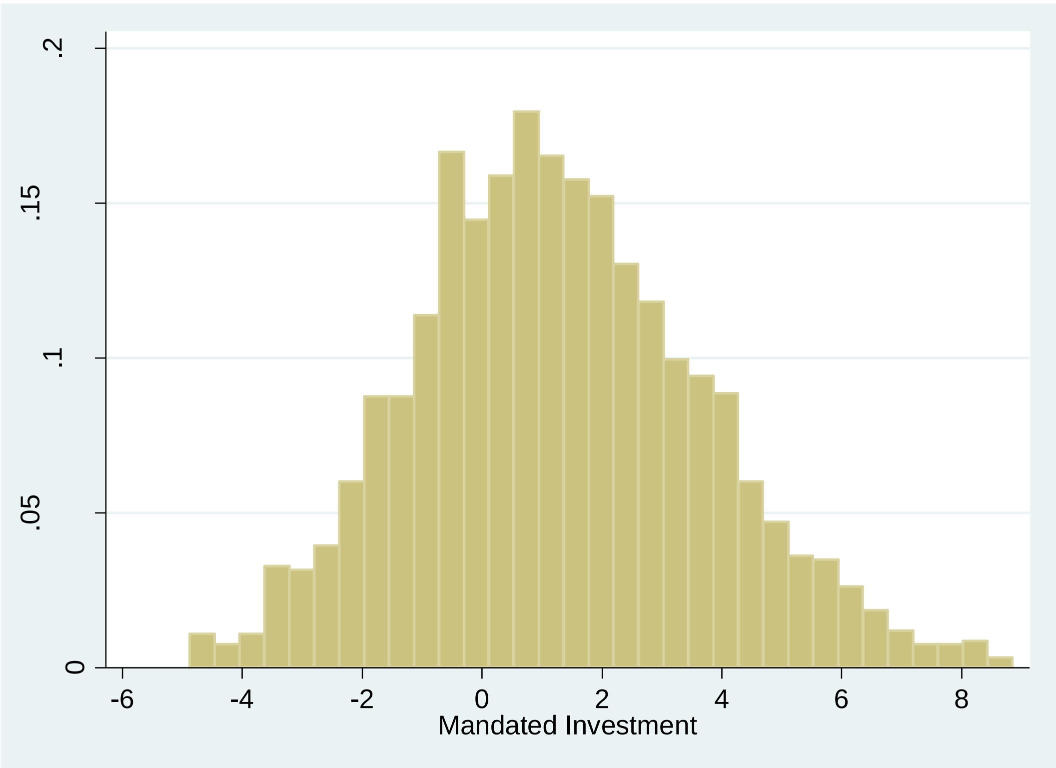

Figure 2: The Distribution of Mandated Investment

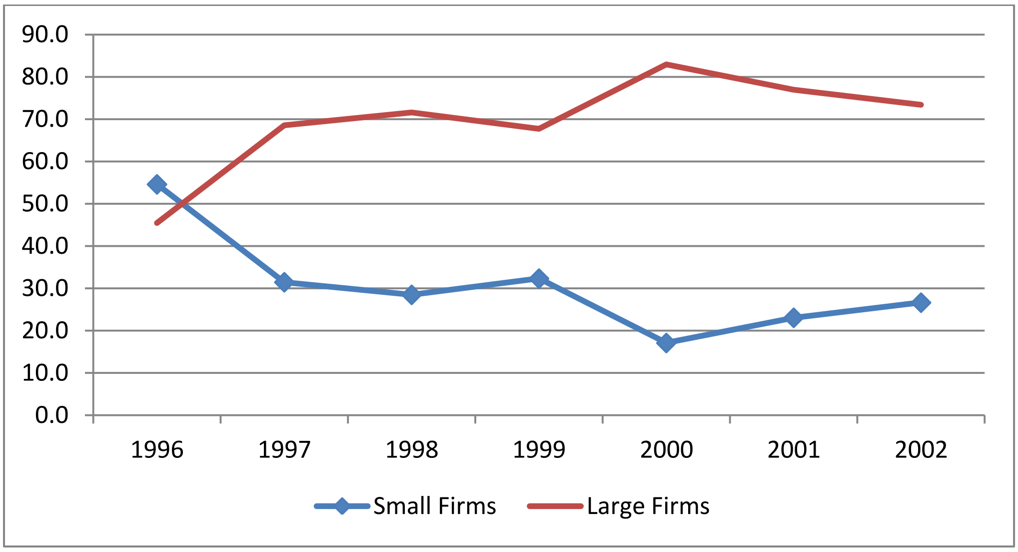

Figure 3: Shares of Small and Large Firms in Total Private Manufacturing Investment

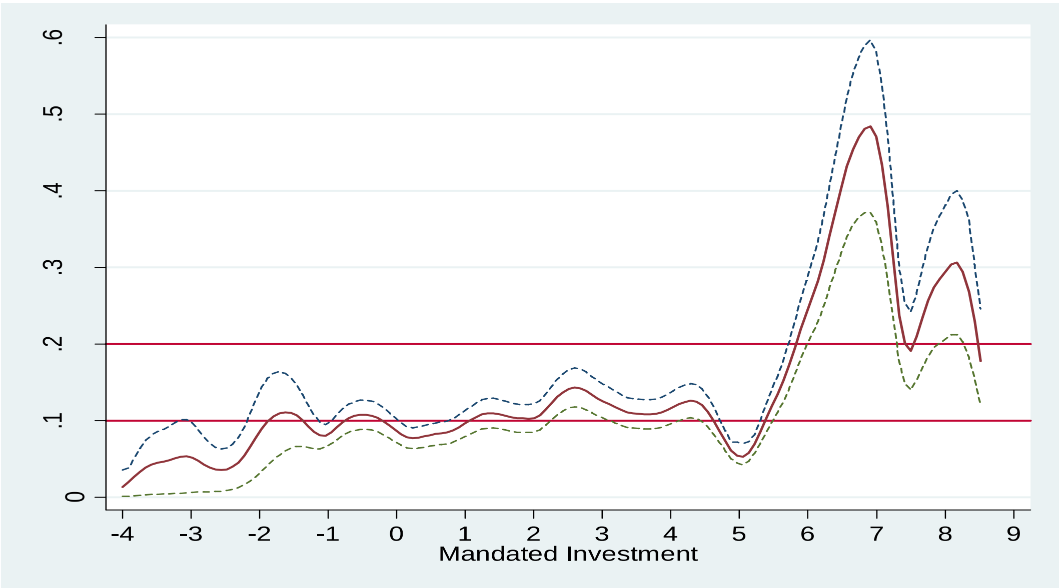

Figure 4: Nadaraya-Watson Kernel Regression for Private Sector Firms

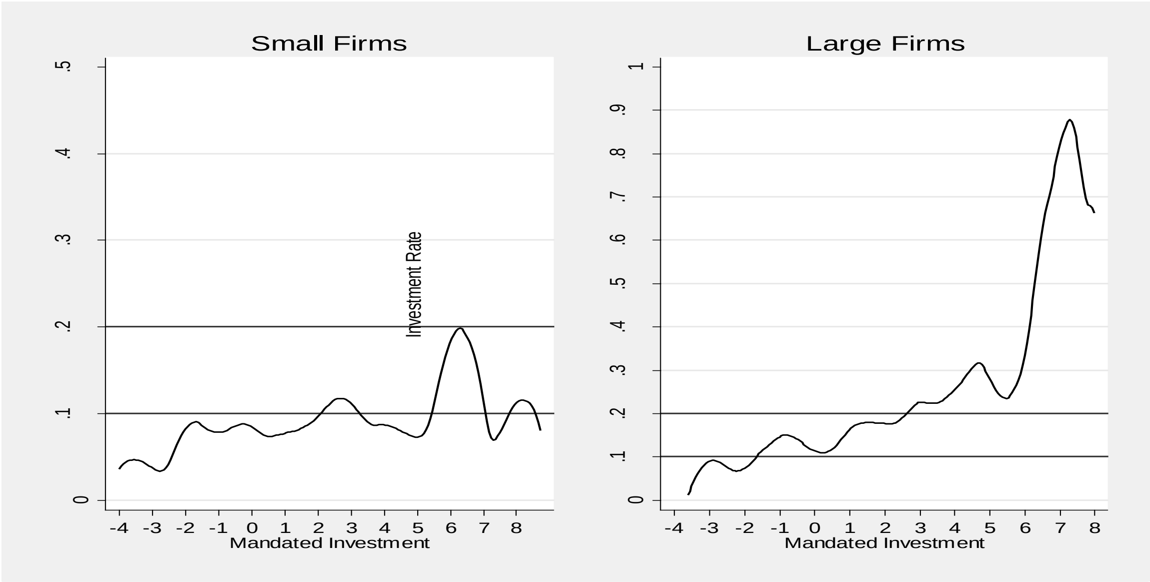

Figure 5: Nadaraya-Watson Kernel Regression for Large and Small Private Firms

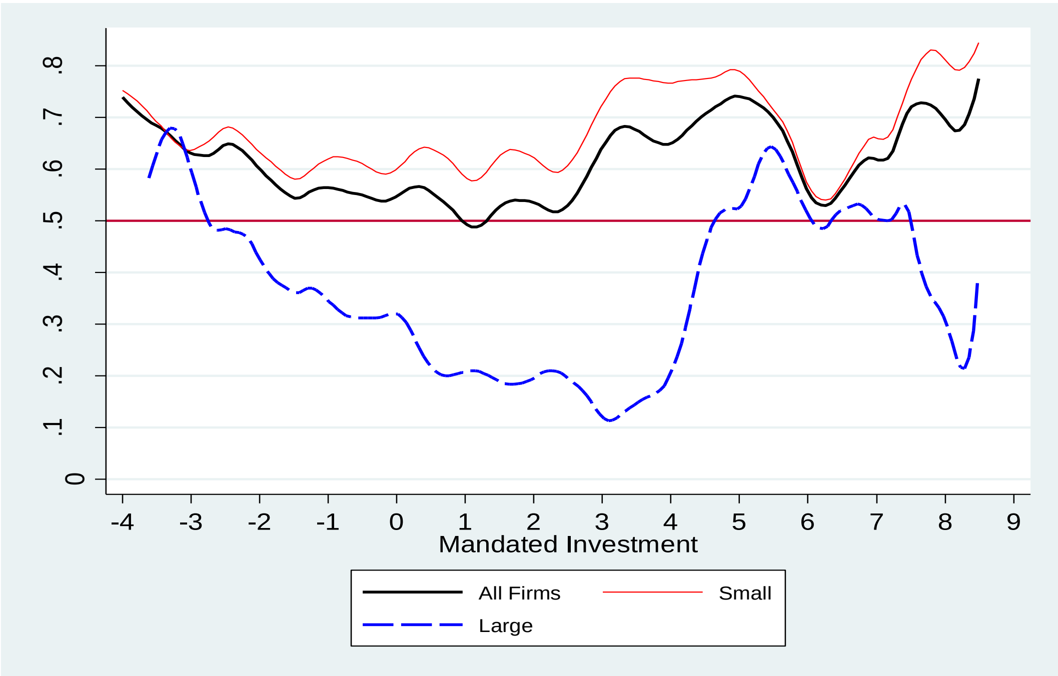

Figure 6: The Incidence of Zero Investment Conditional on Mandated Investment

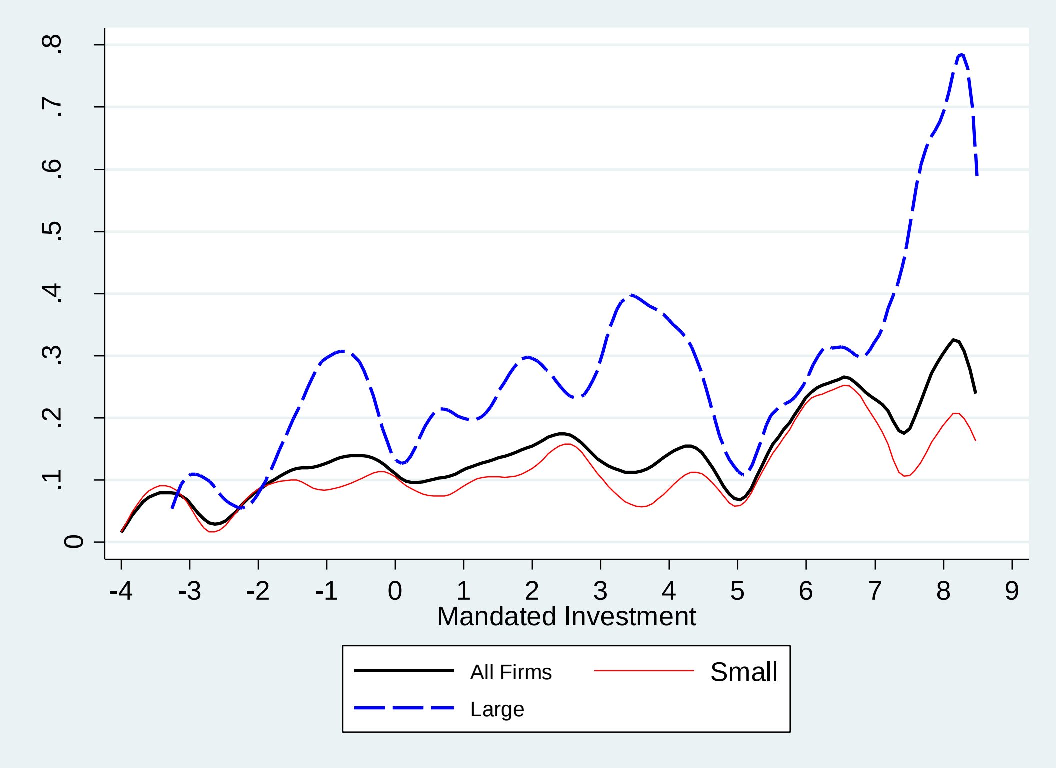

Figure 7: The Incidence of Lumpy Investment Conditional on Mandated Investment

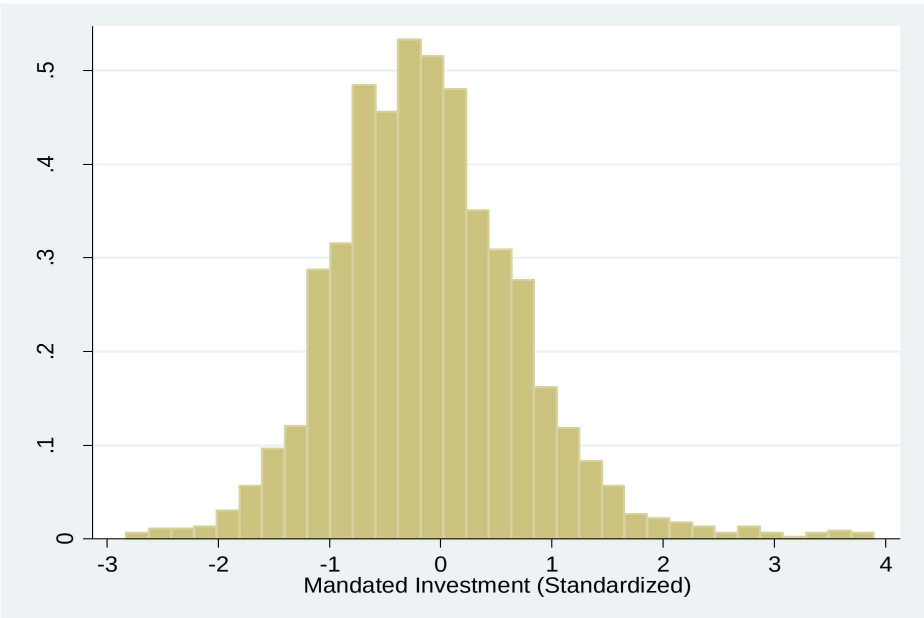

Figure A1: Standardize Mandated Investment

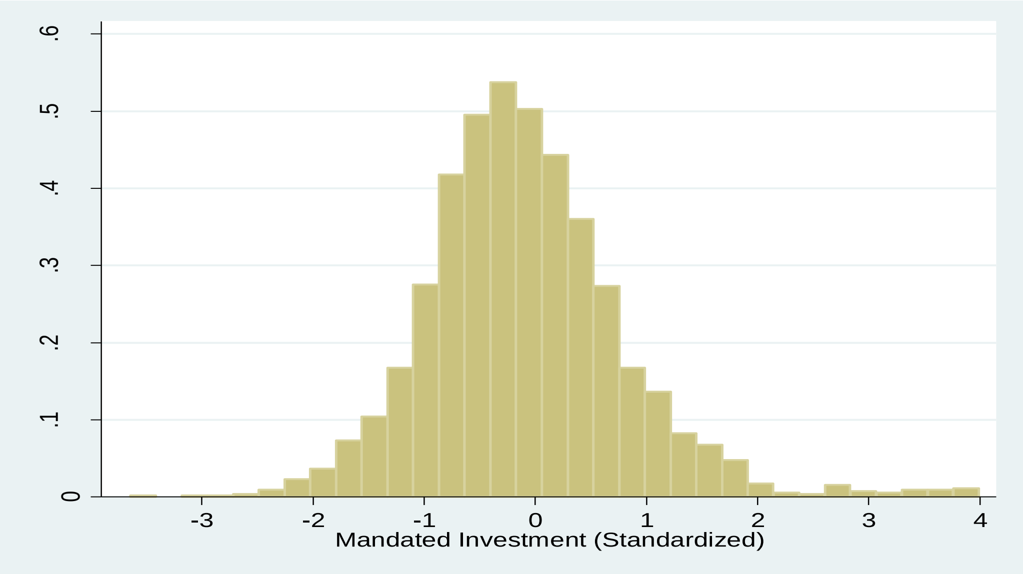

Figure A2: Standardize Mandated Investment with Firm Specific *di*

Table 1: The Distribution of Investment by Industry

	Fraction of Firms (%)					Share in Total Investment (%)			Number of Firms
	IR<0	IR=0	0<IR≤10%	10<IR≤20%	IR>20%	0<IR≤10%	10<IR≤20%	IR>20%	
Food & Beverage	0.4	67.2	20.5	4.4	7.6	12.3	16.0	71.7	688
Textile & Garments	1.1	62.4	17.5	4.2	14.8	6.2	13.8	80.0	189
Leather & Footwear	0.0	48.4	20.6	12.1	18.8	7.3	13.2	79.4	223
Wood & Furniture	1.8	58.8	24.0	4.1	11.3	11.0	7.0	82.0	488
Printing & Paper	1.7	53.0	22.9	5.9	16.5	5.0	2.4	92.6	236
Chemical & Plastic	1.8	49.1	22.6	6.6	20.0	7.6	6.0	86.4	275
Non-Metal	2.0	64.0	19.4	5.3	9.3	8.8	40.2	51.0	247
Metal	2.7	51.3	28.9	3.7	13.4	12.4	3.2	84.4	187
Machinery	2.5	67.1	11.4	10.1	8.9	9.2	7.1	83.7	79
Manufacturing Sector	**1.3**	**59.0**	**21.6**	**5.6**	**12.5**	**9.5**	**11.1**	**79.3**	**2612**

Source: Author's Computation Based on CSA's Ethiopian Manufacturing Census.

Note: The numbers add up to 100% row wise.

Table 2: The Distribution of Investment by Firm Size (%)

Number of employees	IR<0	IR =0	0 < IR≤ 10%	10<IR≤20%	IR>20%	Number of Firms
<50	1.2	66.0	18.7	4.6	9.5	2087
	-	-	10.7	9.0	80.3	100%
≥50	1.9	31.4	33.0	9.5	24.2	525
	-	-	9.3	11.7	79.0	100%
Total	1.3	59.0	21.6	5.6	12.5	2612
	-	-	9.6	11.1	79.3	100%

Source: Author's Computation Based on CSA's Ethiopian Manufacturing Census.

Note: The upper numbers represent the fraction of firms in each investment rate category while the lower numbers represent the share in total investment of firms in that category. Numbers in each row add up to 100%.

Table 3: System GMM estimates of investment rate

	All Firms		Small		Large	
IR_{it-1}	0.0694 (0.0161)	0.0611 (0.0170)	0.0921 (0.0144)	0.0856 (0.0158)	-0.0440 (0.0050)	-0.0334 (0.0068)
MI_{it}	0.0084 (0.0050)	-0.0074 (0.0349)	0.0129 (0.0033)	0.0230 (0.0224)	0.0025 (0.0063)	0.0233 (0.0189)
MI_{it}^2	0.0015 (0.0018)	0.0018 (0.0027)	0.0001 (0.0012)	-0.0022 (0.0017)	0.0107 (0.0018)	0.0126 (0.0028)
π_{it-1}	-0.0036 (0.0036)	0.0006 (0.0045)	-0.0053 (0.0022)	-0.0018 (0.0029)	0.0030 (0.0020)	-0.0040 (0.0024)
σ_{it}^D	-0.0394 (0.0223)	-0.0785 (0.0422)	-0.0126 (0.0176)	-0.0225 (0.0318)	-0.0330 (0.0212)	-0.0466 (0.0315)
σ_{it}^S	-0.0197 (0.0049)	-0.0425 (0.0096)	-0.0130 (0.0043)	-0.0110 (0.0064)	-0.0232 (0.0036)	-0.0155 (0.0047)
$MI_{it} * \sigma_{it}^D$		0.0048 (0.0205)		-0.0102 (0.0139)		-0.0232 (0.0130)
$MI_{it} * \sigma_{it}^S$		-0.0006 (0.0043)		0.0003 (0.0030)		0.0035 (0.0031)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1424	1424	1133	1133	291	291
Number of Firms	500	500	406	406	94	94
Number of Instruments	36	48	36	48	36	48
Hansen Test(p-value)	54.13 (0.3930)	47.21 (0.4231)	43.75 (0.7853)	35.94 (0.8568)	53.50 (0.4163)	54.19 (0.1905)
M1 (p-value)	0.0017	0.0017	0.0079	0.0073	0.1187	0.1212
M2 (p-value	0.5226	0.5473	0.9433	0.9089	0.2271	0.3718

Source: Author's Computation Based on CSA's Ethiopian Manufacturing Census.

Note: Standard errors in parentheses. M1 and M2 are tests for first and second order autocorrelation in the first difference error term. The Hansen test is the overidentification test for the set of instruments. The instruments include the second, third and fourth lags of all the right hand side variables for the difference equation and all possible lags of the first differences of the same in the levels equation.

Table 4: System GMM estimates of investment rate – sample splits based on firm size and scope of secondhand market for capital goods

	Without Secondhand Markets		**With Secondhand Markets**	
	Small	**Large**	**Small**	**Large**
IR_{it-1}	0.1058 (0.0133)	-0.0807 (0.0071)	0.0074 (0.0058)	-0.0297 (0.0302)
MI_{it}	0.0303 (0.0238)	0.0785 (0.0133)	-0.0409 (0.0116)	0.0760 (0.0141)
MI_{it}^{2}	-0.0025 (0.0030)	-0.0124 (0.0013)	-0.0034 (0.0008)	0.0117 (0.0012)
π_{it-1}	0.0023 (0.0031)	0.0009 (0.0014)	0.0096 (0.0008)	-0.0092 (0.0061)
σ_{it}^{D}	-0.0072 (0.0323)	-0.1222 (0.0187)	-0.0009 (0.0205)	0.2642 (0.0366)
σ_{it}^{S}	-0.0195 (0.0059)	-0.0446 (0.0026)	-0.0180 (0.0042)	-0.0007 (0.0051)
$MI_{it} * \sigma_{it}^{D}$	-0.0249 (0.0125)	-0.0280 (0.0121)	0.0311 (0.0104)	-0.0280 (0.0084)
$MI_{it} * \sigma_{it}^{S}$	0.0003 (0.0046)	0.0040 (0.0028)	-0.0081 (0.0015)	0.0090 (0.0034)
Year Dummies	Yes	Yes	Yes	Yes
Observations	672	160	461	131
Number of Firms	231	49	175	45
Number of Instruments	48	48	48	48
Hansen Test(p-value)	38.91 (0.7614)	41.85 (0.6469)	44.18 (0.5487)	31.61 (0.9477)
M1 (p-value)	0.0265	0.2346	0.0351	0.0884
M2 (p-value	0.7997	0.1678	0.6558	0.0770

Source: Author's Computation Based on CSA's Ethiopian Manufacturing Census.

Note: Standard errors in parentheses. M1 and M2 are tests for first and second order autocorrelation in the first difference error term. The Hansen test is the overidentification test for the set of instruments. The instruments include the second, third and fourth lags of all the right hand side variables for the difference equation and all possible lags of the first differences of the same in the levels equation.

Table 5: System GMM estimates of investment rate – sample splits based on firm size and product market structure

	Competitive Markets		Concentrated Markets	
	Small	Large	Small	Large
IR_{it-1}	0.0648 (0.0101)	0.0206 (0.0061)	0.0687 (0.0123)	0.0035 (0.0114)
MI_{it}	0.0162 (0.0073)	0.0476 (0.0106)	-0.0105 (0.0160)	-0.1238 (0.0170)
MI_{it}^2	-0.0040 (0.0010)	0.0022 (0.0012)	-0.0014 (0.0021)	0.0099 (0.0013)
π_{it-1}	0.0066 (0.0019)	0.0009 (0.0016)	-0.0076 (0.0033)	-0.0078 (0.0014)
σ_{it}^D	0.0547 (0.0176)	-0.0463 (0.0326)	-0.0536 (0.0247)	-0.0017 (0.0253)
σ_{it}^S	0.0099 (0.0046)	-0.0103 (0.0048)	-0.0386 (0.0060)	-0.0145 (0.0042)
$MI_{it} * \sigma_{it}^D$	-0.0243 (0.0063)	-0.0087 (0.0106)	0.0073 (0.0100)	0.0707 (0.0178)
$MI_{it} * \sigma_{it}^S$	-0.0060 (0.0014)	0.0055 (0.0015)	-0.0049 (0.0034)	-0.0306 (0.0022)
Year Dummies	Yes	Yes	Yes	Yes
Observations	603	333	557	315
Number of Firms	234	88	183	83
Number of Instruments	48	48	48	48
Hansen Test(p-value)	51.35 (0.2729)	40.74(0.6914)	30.36 (0.9634)	54.16(0.1912)
M1 (p-value)	0.0441	0.1370	0.0278	0.0581
M2 (p-value	0.8394	0.5150	0.9842	0.6876

Source: Author’s Computation Based on CSA’s Ethiopian Manufacturing Census.

Note: Standard errors in parentheses. M1 and M2 are tests for first and second order autocorrelation in the first difference error term – the null hypothesis is that there is no autocorrelation. The sargan test is the overidentification test for the set of instruments. The instruments include the second, third and fourth lags of all the right hand side variables and all possible lags of the first differences of the same in the levels equation.

Table 6: System GMM estimates of investment rate without lagged investment rate– sample splits based on firm size and scope of secondhand market for capital goods

	Small	Large	No Secondhand Mkt		Secondhand Mkt	
			Small	Large	Small	Large
MI_{it}	0.0141 (0.0035)	0.0839 (0.0033)	0.0105 (0.0029)	0.1295 (0.0072)	0.0146 (0.0018)	0.0221 (0.0127)
MI_{it}^2	-0.0010 (0.0002)	-0.0033 (0.0001)	-0.0009 (0.0002)	-0.0066 (0.0002)	-0.0008 (0.0001)	0.0155 (0.0008)
π_{it-1}	0.0010 (0.0010)	-0.0192 (0.0003)	-0.0012 (0.0008)	-0.0172 (0.0006)	0.0005 (0.0003)	0.0050 (0.0025)
σ_{it}^D	0.0438 (0.0240)	0.0240 (0.0058)	0.0726 (0.0175)	0.0962 (0.0153)	0.0073 (0.0090)	0.0517 (0.0288)
σ_{it}^S	-0.0084 (0.0043)	-0.0653 (0.0013)	-0.0092 (0.0029)	-0.0673 (0.0053)	-0.0082 (0.0020)	-0.0261 (0.0066)
$MI_{it} * \sigma_{it}^D$	0.0035 (0.0032)	-0.0318 (0.0022)	-0.0085 (0.0031)	-0.0771 (0.0035)	0.0073 (0.0017)	-0.0027 (0.0043)
$MI_{it} * \sigma_{it}^S$	0.0004 (0.0006)	0.0016 (0.0004)	-0.0007 (0.0007)	-0.0040 (0.0013)	-0.0002 (0.0002)	0.0157 (0.0019)
Observations	1973	483	1105	271	868	212
Firms	657	134	339	67	318	67
Instruments	42	42	42	42	42	42
Hansen test	72.32 (0.6560)	64.71 (0.4120)	66.58 (0.8229)	94.77 (1.00)	61.28 (0.4331)	88.41 (1.00)
M1 (p-value)	0.0003	0.0154	0.0027	0.1234	0.0404	0.0289
M2 (P-value)	0.3768	0.2199	0.4273	0.1116	0.6575	0.9915

Source: Author's Computation Based on CSA's Ethiopian Manufacturing Census.

Note: M1 and M2 are tests for first and second order autocorrelation in the first difference error term – the null hypothesis is that there is no autocorrelation. The sargan test is the overidentification test for the set of instruments. The instruments include the second, third and fourth lags of all the right hand side variables for the difference equation and all possible lags of the first differences of the same in the levels equation.

Table 7: OLS estimate of aggregate investment rate

	(1)	(2)	(3)	(4)
INA_all	-0.0096 (0.1502)	0.0014 (0.1631)		
SPK_all	0.6622 (0.2374	0.7614 (0.1950)		
SPKR_all	0.2065 (0.0612)	0.1688 (0.0471)		
INA_small			-0.1671 (0.0710)	-0.0386 (0.1181)
INA_large			-0.0222 (0.0617)	0.1093 (0.1624)
SPK_small			-0.1670 (0.1660)	0.1196 (0.2011)
SPK_large			0.5441 (0.1011)	0.4580 (0.0988)
SPKR_small			0.0124 (0.0327)	0.0516 (0.0321)
SPKR_large			0.2280 (0.0372)	0.2361 (0.0339)
Constant	-0.0536 (0.1082)	0.0286 (0.1133)	0.0340 (0.0778)	-0.0390 (0.1381)
Year Dummies	No	Yes	No	Yes
Industry Dummies	No	Yes	No	Yes
Observations	53	53	48	48
R-squared	0.4797	0.7193	0.7283	0.8162

Source: Author's Computation Based on CSA's Ethiopian Manufacturing Census.

Note: Robust standard errors in parentheses. *INA* and *SPK* stand for the fraction of firms with zero investment (inaction) and with investment spikes, respectively. *SPKR* is the average investment rate for firms with investment spikes. The extensions _all, _small and _large indicate that a particular variable is either measured for all firms in a sector, or for the sub-sample of small or large firms.

Table A1 : Summary Statistics

All Firms	Observation	Mean	Std. Dev	Min	Max
IR_t	2612	0.1026	0.3259	-0.3461	4.8723
MI_{it}	2264	1.5234	3.1974	-7.3112	21.4245
MI_{it}^2	2264	12.5398	36.6987	0.0001	459.0108
π_t	2576	1.5671	4.5742	-56.1212	52.9699
σ_{it}^D	1779	0.5297	0.3149	0.0268	2.0225
σ_{it}^S	3853	-3.5122	1.5873	-11.3508	3.828935
Small Firms					
IR_t	2087	0.0833	0.3034	-0.3388	4.8723
MI_{it}	1832	1.5077	3.2531	-7.3112	20.5644
MI_{it}^2	1832	12.8501	36.7672	0.0002	422.8936
π_t	2051	1.5895	4.7450	-56.1212	52.9699
σ_{it}^D	1386	0.5251	0.3091	0.0268	2.0225
σ_{it}^S	3223	-3.3993	1.5517	-11.3508	3.8289
Large Firms					
IR_t	525	0.1792	0.3942	-0.3461	3.8681
MI_{it}	432	1.5900	2.9522	-4.5689	21.4245
MI_{it}^2	432	11.2237	36.4200	0.0001	459.0108
π_t	525	1.4793	3.8378	-26.1838	44.0196
σ_{it}^D	393	0.5461	0.3345	0.0293	1.8276
σ_{it}^S	630	-4.0896	1.6423	-10.7823	1.7810

Source: Author’s Computation Based on CSA’s Ethiopian Manufacturing Census.

Table A2: The Probability of an Investment Spike - Random Effects Panel Logit Estimates

	(1)	(2)	(3)	(4)
p1	0.0199 (0.2894)	0.1092 (0.3116)	0.1588 (0.3033)	0.2324 (0.3261)
p2	-0.1644 (0.3293)	-0.3468 (0.3700)	-0.3308 (0.3665)	-0.2913 (0.4083)
p3	-0.7214 (0.4085)	-0.5365 (0.4365)	-0.5493 (0.4358)	-0.6634 (0.4893)
p4	-0.4160 (0.4250)	-0.4884 (0.4762)	-0.5283 (0.4780)	-0.5705 (0.5490)
p5	-1.2786 (0.6124)	-1.1900 (0.6764)	-1.1671 (0.6851)	-0.8549 (0.7654)
i_mandated		0.2178 (0.0519)	0.1890 (0.0495)	0.2982 (0.0623)
i_mandated_sqr		-0.0224 (0.0066)	-0.0189 (0.0062)	-0.0233 (0.0065)
ln(firm size)			0.6124 (0.0943)	0.6148 (0.0985)
ln(firm age)			-0.1173 (0.0871)	-0.1617 (0.0893)
Constant	-2.4432 (0.1298)	-2.5441 (0.1590)	-4.1960 (0.4015)	-4.8805 (0.5800)
Observations	2611	2241	2241	2241
Firms	818	687	687	687

Source: Author’s Computation Based on CSA’s Ethiopian Manufacturing Census.

Note; Standard errors in parentheses. P1 to P5 are dummy variables indicating the number of years since the previous episode of lumpy investment and correspond to years 1 to 5.