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Abstract

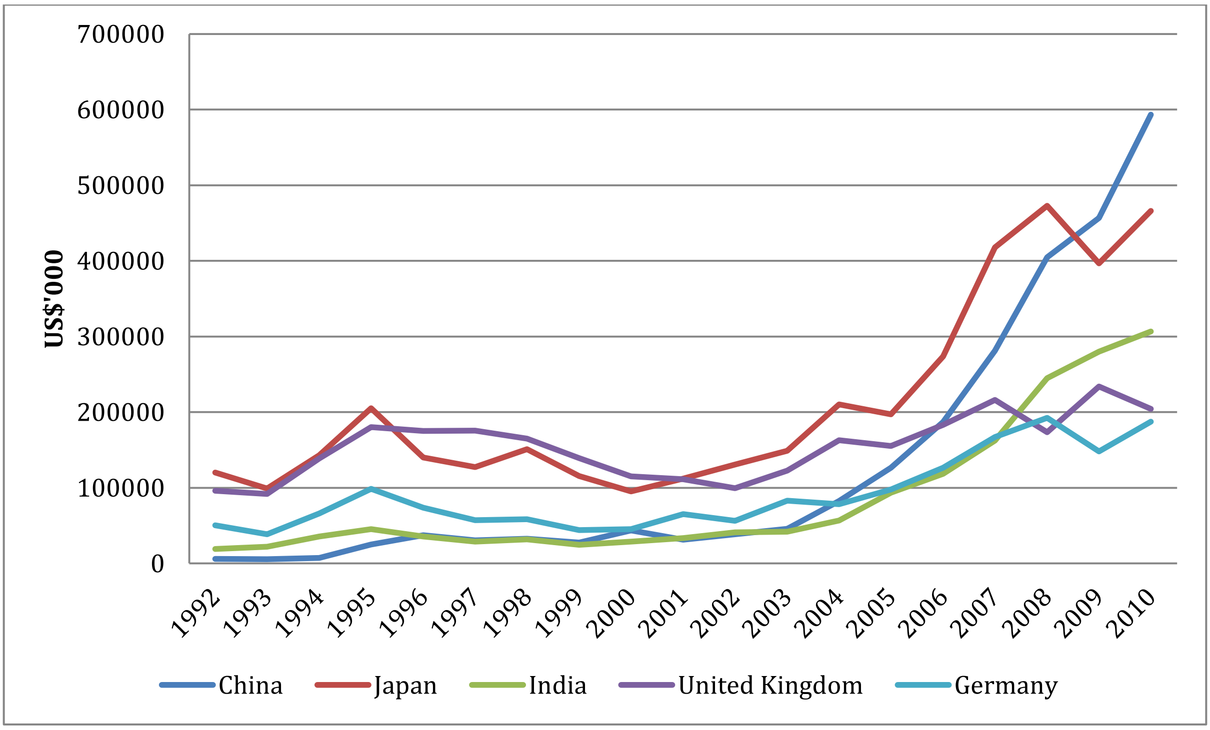
Kenya has started to rely significantly on technologies developed in developing countries particularly China rather than those from advanced countries such as the United Kingdom, Germany and Japan. Using data from furniture manufacturing firms in Kenya, the paper compares the investment cost and the scale characteristics of the technologies (machines and equipment) from China with those from advanced countries and Kenya. By examining the characteristics of the firms that have invested in technologies from various sources, the paper concludes that the technologies from China and Kenya have lessened entry barrier (specifically high capital cost) for new firms, compared to advanced country technologies. Chinese technology appears to serve as an entry mode more than the Kenyan technology. In terms of barriers to entry, therefore Chinese and Kenyan technologies appear to be more appropriate for Kenya (and more generally developing countries) than advanced country technology.

Keywords: Kenya, China, Advanced Countries, Technology, Furniture making, Barriers to entry

1. Introduction

Industrialisation and agricultural mechanisation efforts since Kenya's independence have largely relied on imported technologies especially those from advanced countries (Meilink, 1982; Ikiara, 1984; Renny, 2011). Reliance on imported technology from advanced countries appears to prevent an inclusive growth process to occur. The high industrial growth in Kenya in the 1960s, for example, largely served the interest of a few people in the formal sectors of the economy, much to the disadvantage of the majority in the informal sectors (ILO, 1972). This has been associated with the fact that industrial policies in the 1960s and 1970s supported import substitution industrialisation, which inadvertently promoted the use of imported technology (Ikiara *et al*., 2004; Coughlin and Ikiara; 1988). Data from UN Comtrade confirm that until recently Kenya has depended mostly on imported technology from advanced countries such as The United Kingdom, Japan and Germany. Figure 1 depicts the value of Kenya's import of machinery and transport equipment from five leading sources in 2010. The figure shows that the above-named advanced countries were the major sources of Kenya's importation of machinery until the mid-2000s when China started to emerge as a major source. In fact, imports from China surpassed all the other main sources in 2009, suggesting a disruption of the pecking order of technology transfer to Kenya. Thus, given that China is a developing country, we are now observing a situation where Kenya has started to rely significantly on technologies developed in the context of a developing country.

Figure 1: Kenya's major sources of machinery and transport equipment import



Source of data: UN COMTRADE accessed on 27 March 2012

Although Kenya has relied much on advanced country technologies, the literature on appropriate technology argues that technologies from advanced countries are generally not appropriate for operating conditions in developing countries. The argument is that these technologies target high-income consumers, are highly capital and skill intensive and for realising scale economies with much reliance on sophisticated infrastructure (Kaplinsky *et al*., 2009). Consequently, it is argued that when technologies from advanced countries are transferred "wholesale" to developing countries, as it has occurred over the years (for example, under Kenya's import substitution industrialisation), several structural problems are created in the recipient economies (Stewart, 1982). The characteristics of the technologies reduce the much needed employment creation, lead to limited use of local inputs and sub-optimal growth outcomes, making inefficient use of local factors (Kaplinsky, 1990; Bhalla; 1985; Stewart, 1982). Such technologies also skew production to meeting the needs of high-income consumers who form an insignificant proportion of a developing country's population. Moreover, the industries using such technologies coil into enclaves, as they tend to have limited linkages with traditional sectors and in their developed stages of operations they undermine informal and/ or traditional sectors (Kabecha, 1999).

The highly capital intensive nature of such technologies which require high financial commitment can also serve as a barrier to entry for new firms (Karakaya, 2002), particularly for many that would operate in the informal sector of the economy. Such barriers to entry are structural in nature rather than being the result of the strategic behaviour of existing firms although they can influence patterns of strategic behaviour (OECD, 2006). High capital cost in terms of the absolute magnitude of investment and the cost of borrowing money to finance technology acquisition or generally market entry can serve as a deterrent to start ups or potential entrants. This is especially true when a significant part of the costs is likely to be sunk costs and in the absence of well-functioning financial markets (OECD, 2006). Several empirical studies (e.g. Gschwandtner and Lambson, 2002; Hölzl, 2003) have identified sunk cost as a major factor limiting entry for new firms.

The idea or theory of barriers to entry, of which the trailblazer, Bain (1968 – cited in McAfee *et al.* 2004), defines as anything that allows an already-existing firm to realize abnormal profits without having to attract new firms has been expanded. Caves and Porter (1977) argue that Bain's theory is limited because it concentrates only on the situation where a firm producing nothing (i.e. when the firm is not established) moves into production. They therefore extended Bain's idea into a more general theory of mobility in which firms that are already in an industry can face barriers that prevent them from moving from one segment of the industry to another. For instance, informal sector firms in the furniture industry may face barriers to become formal sector firms. Several empirical studies have consequently examined the importance of mobility barriers and found sunk cost to be a major factor. For example, Hölzl's (2003) used a 14-year panel data on Austrian Manufacturing firms and confirmed the relevance of sunk cost as a mobility barrier.

In this paper, I use data from furniture manufacturing firms in Kenya to examine the technologies from China by comparing them to those from advanced countries and Kenya with respective to the financial or capital cost requirement and the scale characteristics of the technologies. Moreover, the characteristics of the firms that have invested in the technologies are examined in order to determine whether the firms that have invested in the Chinese technology are different from those that have invested in technologies from other countries. The overall objective is to determine whether Chinese technology has lessened the barrier to entry in the furniture manufacturing industry in Kenya, compared to technologies from Kenya and advanced countries. In terms of barriers to entry, the analysis therefore indicates the extent to which Chinese technology may be more appropriate for Kenya and for that matter developing countries than other technologies or vice versa. It should be emphasised that while the paper concentrates on manufacturing technology, its main focus is on machines used for manufacturing furniture. In other words, other forms of technology such as process techniques and organizational forms are not considered in this paper. It is also important to mention that the machines used in the Kenya's furniture industry, and thus those considered in this paper, are stand-alone light-duty machines.

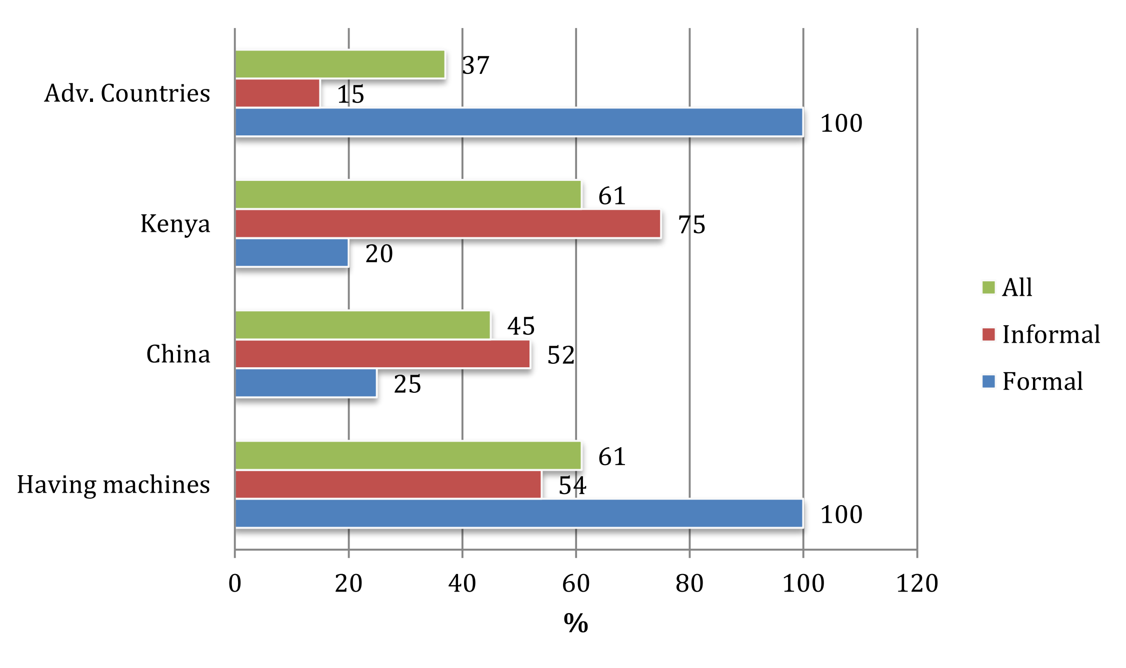
The rest of the paper is organized as follows: Section 2 presents a description of the data used for the analysis. Section 3 compares the cost and scale of the machines from China and the other two sources while Section 4 analyses the relationship between a firm's decision to invest in machines from a source and the characteristics of the firms. The last section concludes the discussion.

2. Data

The data for the analysis were obtained from interviews with 131 furniture-manufacturing firms operating in two cities (Nairobi and Kisumu) in Kenya between August 2012 and January 2013. The furniture manufacturing firms in these two locations generally tend to cluster around specific locations, of which three were selected from Nairobi and one from Kisumu, which has only one major location for all the firms operating in that city. The locations for Nairobi were Industrial Area, Ngong Road and Gikomba Market. The firms from Kisumu, Ngong Road and Gikomba were randomly and systematically selected from their respective sampling frame developed by listing all the firms operating in those locations. Because the firms in the Industrial area were highly interspersed, listing became difficult so they were selected based on convenience and willingness to participate in the study. Twenty of the Industrial Area firms were interviewed while 53, 25 and 33 were respectively from Ngong Road, Gikomba Market and Kisumu. The firms in the industrial area are relatively large in scale, and by and large, they constitute the formal sector of the furniture manufacturing industry while those in the other locations may be described as informal sector firms.

A feature of the data worth noting is that not all the firms interviewed have invested in the light-duty machines. Some of them specifically those in the informal sector have invested only in manual and/or power hand tools. Figure 2 indicates that 61% all the firms interviewed have invested in machines. For the informal sector firms, however, 54% have invested in these machines compared to 100% for the formal sector firms. The figure also shows that all the formal sector firms have investment in machines from advanced countries while the informal sector firms tend to rely mostly on Kenyan machines (locally referred to as 'jua kali' machines) and Chinese machines.

Figure 2: Investment in machines from China, Kenya and advanced countries by sector



Source: Author's field data, 2012/2013

Information on the acquisition cost and scale characteristics of the machines were collected in a second round of interviews with a purposive sample of the firms selected from the 131 that were initially interviewed. There is a wide range of light-duty machines used in the furniture industry and examples are planing machine, band saws, lathe and circular saw. In this paper, I use the data collected on planing machines to illustrate how distinctive the Chinese technology found in Kenya furniture industry are from the others specifically with regards to scale and investment requirement. Although the focus here is on the planing machines, the results can be easily generalised to other types of machines because I found that in relative terms the differences across the sources for the other machines are comparable to the those of the planing machine. It should however be noted that the planing machine discussed in this paper tends to have auxiliary functions such as ripping, crosscutting and boring.

3. Cost and scale characteristics of technologies

Table 1 presents the acquisition cost and the annual capital consumption per worker for planers from the three sources – China, Kenya and advanced countries. Rather than relying on the historical data on acquisition cost from the firms, the current purchasing costs of the machines are used for the computations and comparisons. I obtained the current acquisition cost through a triangulation between data on perceived replacement cost of the machines from the manufacturing firms, prevailing market prices from marketing and distribution firms and the Internet. These sources helped to provide estimates about how much the machines would cost if they were to be acquired at time of the survey. This triangulation was done because the relevant decision making variable when choosing between different sources of machines is the cost the firm perceive to incur on the basis of the prevailing internal and market information about cost at the time of making such decisions.

Table 1: Acquisition cost, capital consumption per annum and labour input for planers

Variable description	China	Kenya	Adv. (New)	Adv. (Used)
Current purchasing cost (USD)	1118	1000	11765	7647+
Investment (capital consumption per year - USD)	111.8	67	327	264
Annual capital consumption/worker	55.9	33.5	163.5	132
Number of workers required	2	2	2	2

+The value is for the price of a machine with 16-inch wide thicknesser while the corresponding values for the other sources are for planers with 12-inch thicknesser

Table 1 shows a large difference between the acquisition cost of Chinese machines and those of the advanced country machines while Kenyan machines are slightly cheaper than the Chinese machine. Thus, the Chinese machines are far cheaper than the advanced country machines and tend to serve as viable alternatives for the firms particularly those operating in the informal sector. A statement from an informal sector operator who has invested in a Chinese planing machine provides more evidence:

> This Chinese machine has really helped me … This is the machine for the poor man or carpenter. The English ones are out of reach. An English machine of about this standard will go for about 600,000 [Kenyan] shillings[1] and this is just around 80,000 [Kenyan] shillings so you see that much difference and I recommend other people to go for it and I will buy another one if I had the money (Field interview, 2012).

Another person also said:

> The best for us is the second hand ones from England but they are very expensive ... But when you start with the cheapest, you can go saving small, small until you get enough money to buy the best. So, I am hoping to buy the England second hand planing machine one day (Field interview, 2012).

Thus, the cheap Chinese and Kenyan machines have been helpful to the informal sector operators who cannot afford second hand machines from advanced countries let alone brand new ones. They however hope to switch to advanced country machines as they accumulate more financial resources. Such hopes can materialise particularly in the light of the following testimony from a formal sector operator employing 90 workers: “I started more or less as jua kali [informal sector firm] and I had only jua kali machines. But as the work progressed I was able to buy second hand machines from Europe. Now I have only two jua kali machines at my workshop” (Field interviews, 2012).

[1] The exchange rate in Kenya at the time of the data collection was about 85 Kenyan shillings per USD 1.

It should be noted that the Chinese machines (and to some extent the Kenyan machines) require more maintenance than those from advanced countries. However, this does not seem to erode the cost advantage of the Chinese machines. A statement from a respondent with investment in Chinese planer confirms this:

> … it is cheap and the England one is more expensive just that it needs more maintenance. But if you look at the cost of maintenance plus the purchase, it is still more economical than the England machine. So it is better to go for this one. I am comfortable with this planing machine and next time when I want to buy a planing machine of this type I will still buy the one from China. (Field interviews, 2012)

Table 2 provides information on the scale of the planing machines. Mainly relying on horse power, the number of phases for power connection and physical size, the table indicates that on average the Chinese machines found in Kenya's furniture industry tend to have relatively low capacity or scale compared to the advanced country machines and even the Kenyan machines. For all the measures presented in Table 2, those for the Chinese planing machines are much lower than those of the advanced country machines. The horse power of the motor on the Kenyan planing machine is also higher than the average for those on the Chinese planing machine. Typically, a Chinese planing machine found in the furniture industry has a 12-inch wide thicknessing table and 1-phase motor with 3 horse power compared to at least 16-inch wide thicknessing table, 3-phase motor of about 5.5 horse power for a typical advanced country planer. The difference in the physical scale of the machines is important since several studies such as Kaplinsky (1990), Majumdar and Vankataraman (1998) and Hall and Khan (2001) have provided evidence supporting the importance of scale for investment decision of firms.

Table 2: Scale/ capacity characteristics of planers

Variable description	China	Kenya	Adv. Country
Width of thicknesser+	12	12	18
Horse power	3.1	5	6
Phases	1.2	1	3.0
Number of planers	20	1	9

+The size of the thicknesser, measured in inches, is a proxy measure for the physical size of the planer.

It should however be noted that the scale of the Chinese machine is sometimes too low for the work of the operators including those in the informal sector. Consequently, they sometimes modify or "re-engineer" the Chinese machine. The re-engineering or modification, also called "overhauling" by the respondents, involves replacing some parts of the machine such as the bushes, switches and bearings with those that are more robust, which in most cases are second hand parts from advanced countries. Most importantly, the motors are usually replaced with those that have higher horse power. However, the additional cost of modification is very insignificant in relations to the acquisition cost of the advanced country planing machines. An important implication of this is that if we can refer to the Chinese machines as an innovation for the poor, as a respondent indicated and was quoted earlier in this section, then the poor in Kenya are also doing further innovation on the machines. This innovation seems to take two forms rather than being uniform. The first involves only the kind of overhauling described above. The second however appears more subtle: What the firms do is that instead of overhauling, they deactivate the auxiliary functions of the planing machines (such as ripping and boring) so that the work pressure on the machine is reduced and then invest in a saw bench from Kenya.

4. Firm characteristics and adoption of the technologies

Firms are not homogenous but may differ in many ways. They may differ with respect to their objectives, size, knowledge about available technologies, resources available to the firm, which include material inputs and labour of various skills (Stewart, 1982, 1987; and Stewart and Ranis, 1990). For example, a government-owned corporation may have other aims apart from profit maximisation (e.g. employment expansion) compared to a locally owned public enterprise, and this may have implications for technology choice (Stewart, 1982). Thus, the characteristics of firms may influence technology choice since firms are not homogenous in reality.

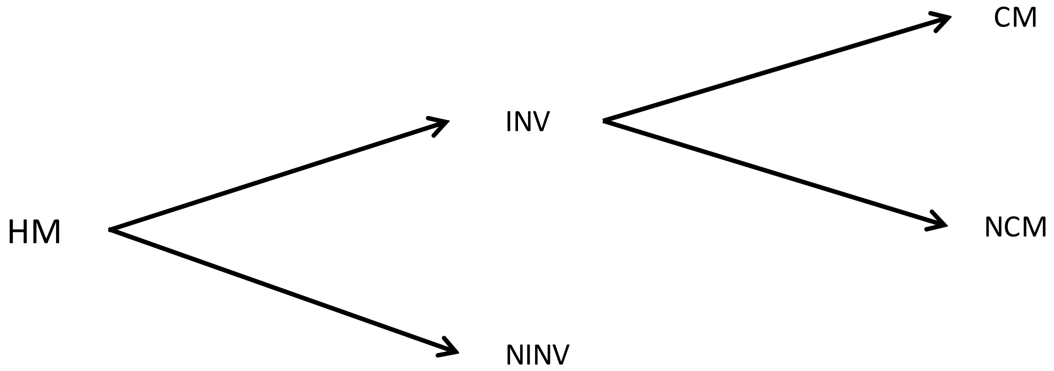
Many other studies including strongly empirical ones point to the fact that firms' heterogeneity has important implications for technology choice. Using empirical data on looms for cotton textile weaving in Korea, Rhee and Westphal (1977) found evidence that firm characteristics (such as size, ownership and location) have implications for the choice between semiautomatic and automatic loom technologies and between domestic looms and imported ones. A recent empirical study by Bertschek *et al.* (2013) on German firms also confirms that firms' heterogeneity can lead to different technology choice. Brandt and Zhu (2005) used survey data on 250 firms in Shanghai to find that a firm's attributes such as age, size and human capital influence its technical capacity, which in turn affects the firm's decision to adopt a technology or not. Brandt and Zhu's study further shows that among firms with the same technical capacity, the ones with better access to cheap bank credit are more likely to embark on larger technology projects and invest more in imported equipment from technologically advanced countries. Similarly, with an empirical analysis based on data from five Latin American countries, Hasan and Sheldon (2013) confirm that firms face credit constraints in technology adoption.

In this section, I examine the characteristics of the firms as correlates of the decision to adopt or invest in the machines from the three sources. This will help determine which types of firms are investing in the technologies from the three different sources and which firms are benefitting from the low-cost Chinese machines. The analysis is done using logit regression models.

The regression models

Investing in technologies (machines) from any of the three sources generally involves a two-stage decision making processes where the firm is confronted with a set of choices at each stage. In the first stage, the firms decides on whether to invest in light-duty machines at all with the outcome that some choose to undertake such investment while others prefer the contrary. Those that choose to invest in the light-duty machines then go on to decide whether to buy machines from a particular source. Thus, investing in Chinese technology for example generally involves two stages of decision making as described in Figure 3. The two stages correspond to two questions the firms were asked to answer during the survey. They were initially asked to indicate whether they have invested in light-duty machines, of which the outcomes may be represented in Figure 3 as INV and NINV, which respectively represent the situations where the firm has undertaken such investment and where the firms has not embarked on such investment. Those who have invested in machines were then asked whether they have invested in Chinese technology or not with the outcomes represented in the figure as CM if the firm has undertaken such investment and NCM if the firm has not invested in Chinese machines. These two decision making process also generally characterise investment in other technologies.

Figure 3: Nature of the dependent variables



Based on the above description of the sequence of decision making, the adoption of technologies from any of the three sources by a firm can be examined in a sequential logit model. Also referred to as sequential response model, continuation ratio logit, model for nested dichotomies or Mare model (Buis, 2011), sequential logit involves estimating a separate logistic regression for each stage of the decision making. The stages are sometimes referred to as transitions since only a proportion of the sample at the previous stage moves to the ensuing stage. In this study, only those who have chosen to invest in machines move to the next stage of deciding whether to invest in a technology from a particular source, say China. As shown in Figure 3, each of the stages involves dichotomous or binary outcomes, of which *success* (i.e. adoption) and *failure* (i.e. non adoption) are respectively ascribed a value of one and a value of zero, and serve as the dependent variables in the various regressions. Hence, for this study they produce the following logit regression models where the outcome depends on a set of independent variables:

$$\boldsymbol{p_1 = \frac{\exp(X\beta_1 + \varepsilon_1)}{1 + \exp(X\beta_1 + \varepsilon_1)}} \qquad (1)$$

$$\boldsymbol{p_2 = \frac{\exp(X\beta_2 + \varepsilon_2)}{1 + \exp(X\beta_2 + \varepsilon_2)}} \qquad \mathbf{(2)}$$

$$\boldsymbol{p_3 = \frac{\exp(X\beta_3 + \varepsilon_3)}{1 + \exp(X\beta_3 + \varepsilon_3)}} \qquad \mathbf{(3)}$$

Equation 1 corresponds to the first stage for which a firm chooses to invest in light-duty machines while equation 2 also corresponds to the first stage but for the situation where the firm chooses not to invest in light-duty machines. Equation 3 represents the second stage where a firm that has chosen to invest in light-duty machines decides to invest in machines from a source, say China. The number subscripts represent the different equations. β and X respectively represent the matrices for the coefficients and independent variables. P is the matrix of *probability of success.*

Equations 1 to 3 model the adoption of a technology as a function of the characteristics of the firms /operators only, which means that the matrix X contains only variables measuring the firm/operator characteristics. Thus, the characteristics of the technologies or alternatives in the choice set do not enter the regression equations. This is because some of the characteristics such as acquisition and maintenance costs are only observed after the firm has chosen to invest in a machine from a particular source. Moreover, the characteristics of the machines or factors specific to a technology type do not seem to vary across respondents. Quality in terms of the flexibility and the precision of functions of the machines from a particular source found in the furniture industry do not vary across firms. Similarly, purchasing cost cannot vary if markets function perfectly, and in fact I observed only slight variations of the prices of a machine from a particular source across firms retailing the machines in Kenya. Consequently, it is assumed in this study that the effects of the characteristics of the technologies on an individual's choice do not deviate substantially from the average for the sample or population. So, rather than being used as independent determinants of the alternatives as in the case nested logit models (Greene, 2003) the characteristics of the alternatives are regarded as purely intrinsic determinants of the alternatives in this model.

However, the weakness of the model is that the effect of unobserved heterogeneity resulting from variables that may influence the choice but are not included in the model cannot be accounted for (Cameron and Heckman, 1998). In this regard, it should be mentioned that many variables, which may influence the choice do not enter the regression analysis because of two reasons. First, data were not collected on some of the variables because they were difficult to measure (e.g. firm level profit and financial performance in the informal sector). Second and more importantly, the sample size (131) for the regression and particularly for the second stage (80) is not large enough to accommodate a lot of regressors (independent variables), even if all the data were available. The minimum sample size for logit regression should satisfy the condition that the sample size divided by the number of parameters (β) to be estimated should not be less than ten (Hosmer and Lemeshow, 2000). This means that the second stage regression cannot take more than eight regressors. The consequence is that some of the variables for which data is available (including possible interactions between some of them) will also not enter the regression equations.

The impact of the above problem is that it becomes difficult to derive causal relationships between the dependent variables and the regressors used in the analysis. However, the advantage of the regression analysis over simple correlation analysis is that it helps control for some of the extraneous variables that may confound the correlation between the variables.

The independent variables used for the various regression models are measured as described in turns as follows:

a. Log of firm age: Firm age is a continuous variable which means it takes metric values instead of discrete values. All the regression models use log of the firms' ages. This variable is represented in the tables of the results as *Agelog*.

b. Log of firm age squared: Shown in the results as *Agelog2*, this variable is included to capture the likely nonlinear impact that experience which comes through age may have on adoption of technology.
c. Firm size: The size of firm is measured by the total number of employees the firm has, which was also collected as a continuous variable. The log of the variable enters the regression models and it is represented as *firmsize*.
d. Firm's access to finance: Firm's access to credit which is represented in the tables of the results as *Acc_Fin* enters the regression equations as an index of six variables. The index is the First Principal Component which is a linear combination of weighted values of the six variables, derived using Principal Component Analysis (PCA). Detailed discussion on this has been provided in the appendix.
e. City: The city (Nairobi or Kisumu) in which the firms operate enters the models as a dummy variable with a value of one if the firm operates in Kisumu; otherwise zero. It shows up in the tables of results as *Kisumu.*
f. Log of director's age: Also a continuous variable, the log of the age of the operators are used in the regression models and it is represented in the tables of results as *log_dage*.
g. Sex of director: Represented in the results by *female*, sex also enters the regression models as a dummy variable with a value of one when the operator is a female, otherwise zero.
h. Education of operator/director: This variable is represented in the table of the results by *above_basic_sch* and enters the regression models as a dummy variable with a value of one when the operator has more than primary (or basic) education, otherwise zero.
i. Marketing and administrative orientation of director: Represented in the tables of results as *No_bus_card*, this variable is proxied by whether the operator has a business card or not. It is also a dummy variable which takes a value of one if the operator does not have a business card and zero if otherwise.
j. Ownership structure: This is a discrete variable which enters the regression models with a value of one if the firm is a sole proprietorship, otherwise zero and it is represented in the results as *Sole*.

An additional qualification with respect to the models is worth mentioning, and that is, the categorisation of firms into formal and informal sectors does not enter any of the regression equations. The reason is that that variable perfectly predicts the probability of a formal sector firm having invested in light-duty machines and those from advanced countries, thus it assumes the answer which I would like to test. It is also highly correlated with other explanatory variables particularly *firmsize* as Table 6 in the appendix shows. Table 7 in the appendix also shows descriptive statistics (averages, percentages or frequencies) of the independent variables used for the regression analysis. Where necessary, reference to some of these statistics will be made when interpreting the results from the regressions.

Estimation method and results

The parameters (β) of the regression equations are estimated using the maximum likelihood method. Table 5 in the appendix shows the regression results. Results on two variants of the regression models for having invested in light-duty machines[2] and for having invested in a

[2] In order to simplify the discussion "light-duty machines" will be referred to as "machines" henceforth.

machine from a particular source (China, Kenya and advanced countries) are presented. Each equation is first estimated with only the log of the firm's age and its square, and in the second case, the other independent variables are included in each of the models. The special interest in the age of the firms is born out of the fact that the age helps to easily determine whether relatively young firms are investing more in the Chinese machines compared to the others, which will help confirm that the Chinese technology serve as a mode of entry. Robust standard errors based on the sandwich estimator of variance (StataCorp, 2009) are obtained for all the regression results reported in Table 5 in the appendix. Below are the interpretations/ discussions of the results.

Firm age

From Table 5 in the appendix, the influence of firm's age in all the models with only the log of firm's age and its square generally do not differ from those with all of the other independent variables. The table shows that both *Agelog* and its square (*Agelog2*) are not statistically significant for a firm having investment in machines (column 1 and 2) but are significant for the investment in machines from China (column 3 and 4), investment in Kenyan machines (column 5 and 6) and investment in advanced country machines (column 7 and 8). This result suggests that age may not have much influence on a firm's decision to invest in machines but it is important for the choice between the various sources for those firms that have invested in machines.

The result also indicates that except for investment in machines, the age of the firm has statistically significant and quadratic relationship with the probability that a firm that has invested in machines will invest in machines from China, Kenya and advanced countries. For investment in Chinese machines, with *Agelog* having a positive sign and its square being negative implies that the probability of investing in Chinese machines on average increases with age up to a given point (about 4.5 years) and falls thereafter as shown in Panel B of Figure 4[3] in the appendix. Similarly and as shown in Panel C of Figure 4, the probability of investing in Kenyan machines on average increases with age up to about 7 years after which it begins to decline. Contrarily, as Panel D of Figure 4 portrays, the probability of investing in advanced country machines initially falls with age and start rising after the firm is about 5 years old, at around the same age at which the probability for investing Chinese machines starts to fall.

The above findings have three important implications concerning the role the Chinese and Kenyan technologies play in the furniture making industry. First, the similar effects of age on the probabilities of investing in the Chinese and Kenyan machines may suggest that generally the technologies from China and Kenya play similar roles and tend to complement each other. Second, the role of these two technologies in the industry has been to lower the entry barrier for entrepreneurs wanting to enter into the furniture making industry or to enhance the degree of automation in the production processes of the existing firms particularly the informal sector firms (i.e. they have reduced mobility barrier). Many of such operators especially those starting businesses in the informal sector are likely to be relatively poor and may not be able to afford the advanced country machines. As was noted under section 3, the operators find the advanced

[3] Each panel in Figure 4 plots the predicted probability from the regression analysis against the log of the firms' age. Taking antilog of the log of firm's age at the optimum of each quadratic produces the actual age of the firm at the various optima. The log of the firm's ages at the respective optima are obtained by taking the first differential of equation 3 with respect to *agelog* (i.e. the slope of the function with respect to *agelog*), setting the resultant equation to zero and solving for *agelog* in the resultant equation. This process is simplified with estimated parameters of the equations provided in Table 5.

country machines to be too expensive. Hence, they buy the cheap Chinese and Kenyan machines but hope to later diversify away from these machines to the ones from Europe as their businesses develop. Third, the optimum age for the Kenyan machines is higher than that for Chinese machines. This may imply that the Chinese machines tend serve as an entry mode more than the Kenyan machines.

City (Kisumu)

This variable is statistically significant and negatively associated with the probability of a firm investing in machines. The variable is also significant in the results for investment in machines from China and Kenya. It shows up with a positive sign in the results for machines from China but a negative sign for machines from Kenya. This means that being in Kisumu is associated with a higher probability of investing in Chinese machines but with a lower probability of investing in Kenya machines compared to the firms in Nairobi. The firms in Kisumu, which are all informal sector firms as indicated in Table 7, seem to have embraced the Chinese technology more than those in Nairobi. Those in Nairobi especially the informal sector ones seem to have relatively high confidence in the Kenya machines. A likely explanation for this is that there are a lot of fabricators of Kenyan machines in Nairobi while it is relatively difficult to find such fabricators in Kisumu.

Firm size

Firm size is statistically significant for the decision to invest in machines but insignificant for the decision to invest in the technologies from a particular source. It has a positive sign in the results for investing in machines suggesting that as the size of the firm (in terms of the number of employees) increases the probability of investing in machines also increase.

Access to finance

My interactions with the firms showed that bank loans (and loans from microfinance companies in the case of the informal sector firms) are not a popular means of financing machine acquisition. Rather, the firms tend to depend largely on internally generated funds. However, it should be noted that a positive relationship with financial institutions such as having a bank account and receiving short-term loans could make some important difference. The results show that access to finance (*Acc-Fin*) is statistically significant in the model for investment in machines but not for the others. The coefficient in the results for investment in machines has a positive sign, which means that firms with high access to finance, as measured by *Acc-Fin*, have high probability of investing in machines. The intuitive explanation is that having a bank account for example may help a firm to save more, thus, with an account a firm may be able to accumulate savings faster to invest in machines. It may also reflect the fact that firms with bank accounts tend to have greater financial resources.

For firms deciding to invest in machines from a particular source, such relationship with financial institutions does not significantly influence their decision. This result appear counterintuitive and may have resulted from the fact that the measure for access to finance did not capture how much a firm is able to leverage from external sources. I did not collect any data including proxies on the amount of loans the firms had taken from financial institutions in any given period. However, to the extent that firms do not depend much on bank loan for acquiring machines gives the conviction that the result would not change much even if the access to finance index or variable captured information about the volume of funds the firms are able leverage from financial institutions. Rather, what could make a major difference would be if the financial institutions could lend to the firms including the informal sector ones at a lower interest cost and with more flexible repayment terms than what they currently offer. Under such circumstances and assuming the influence of all other factors are muted, one could expect that the firms including those in the informal sector to invest more in advanced country machines, compared to the others.

Ownership structure

Ownership structure (*Sole)* is only statistically significant in the results for Kenyan machines and advanced country machines. Thus, being a sole proprietorship rather than a partnership or family-owned business is not significantly associated with the decision to invest in machines and also the decision to invest in Chinese machines. However, it significantly associated with a higher probability of investing in Kenyan machines and a lower probability of investing in advanced country machines. This finding is intuitively intelligible: Kenyan machines are very cheap, thus, an individual can more easily organise financial resources to purchase them while advanced country machines are very expensive, and hence, pooling resources from different individuals who may be relatives makes it easy to undertake such investment. It is interesting to note here that sole proprietorship is the commonest ownership structure among the informal sector firms, while all the formal sector firms are either family-owned businesses or partnership (Table 7).

Operator's marketing and administrative orientation

As noted earlier, operator's marketing and administrative orientation is proxied by *No_bus_card,* which stands for an operator not having a business card. It has a positive coefficient and statistically significant result for investment in machines indicating that not having a business card increases the probability of investing in machines. This result appears counterintuitive and should be interpreted with care, as one would expect that not having a business card should be negatively associated with the probability of investing in machines. However, what it means is that there are a lot of informal sector firms whose operators have business cards but have not invested in machines as well as those whose operators have invested machines but have no business cards. The result is also plausible given that the dependent variable does not take into account the number of machines a firm has.

For those firms which have invested in machines, not having a business card is significantly and positively related with the probability of investing in Kenyan machines while it is significantly associated with a lower probability of investing in Chinese machines. Although not significant, it is also negatively associated with the probability of investing in advanced country machines. What this may suggest is that operators with relatively "modernised" marketing and administrative orientation prefer investing in Chinese and probably advanced country machines to investing in Kenyan machines. Generally, such operators may serve relatively high-income segments of the market, which require high degree of precision. The respondents noted that the Kenyan machines are relatively limited in terms of the precision of the functions compared to the other two.

Operator's level of education

Director's educational level (that is, having more than basic education) is not statistically significant in any of the results, indicating educational level of the operator does not significantly influence the decision to invest in machines and also machines from any of the three sources.

Director's age and sex

The age and gender of the operator appear only in the regression model for investing in machines because the sample sizes for the others are relatively small with limited degrees of freedom. Age has a positive coefficient and it is significantly associated with the decision to invest in machines. Thus, older entrepreneurs tend to have investment in machines than younger ones. This result may be explained in the sense that older individuals might have accumulated savings if they have been in their current business for long time or from their previous vocation, which could be used for investing in machines. Moreover, older people generally tend to have better access to family resources or inheritance and social network, all of which can be used to mobilise resource for investment in machines. The results however show that being a female operator has no significant relationship with whether a firm will invest in machines or not. It should be noted that furniture making in Kenya is a male-dominated sector: Information in Table 7 indicates only 5% of the firms interviewed are female-headed firms.

Bivariate/multivariate probit models for testing complementarity

This section quantitatively test complementarity between investment in Chinese machines and Kenyan machines, which was alluded to earlier. This is done by reestimating the regression equations for the second transition of the choice process depicted in Figure 8.5 for having a Chinese machine and having a Kenyan machine but in a bivariate/multivariate probit model. Bivariate models start with the idea that the error terms in the regression equations for two dichotomous variables (for example, in this case of this thesis, having a Chinese machine and having a Kenyan machine) are correlated (Greene, 2012). Hence, under normality assumption, the two variables are simultaneously modelled (Maddala, 1983). Since we have a third dichotomous dependent variable (i.e. having an advanced country machine), a generalised form of the bivariate model, that is, the multivariate probit model[4] is also applicable or may be more appropriate. I therefore reestimate the regression equations for the second transition using both bivariate probit models (results are reported in Table 8 in the appendix) and multivariate probit models (results reported in Table 9 in the appendix). For the bivariate models, the equations are estimated using the maximum likelihood technique while a simulated likelihood method is used for the multivariate model and robust standard errors are obtained for both results in a way similar to the previous regressions.

Several methods such as simple Chi-square test and simple (product moment) correlation analysis could be used to examine this relationship. What makes the bivariate/multivariate probit models most attractive for this study is that it allows for the calculation of tetrachoric correlation coefficient, examining its significance and making the tetrachoric correlation coeficient conditional on a set of independent variables that may confound the relationship between the two variables (Greene, Undated; Greene, 2012). The tetrachoric correlation coefficient is the correlation coefficient for two binary variables calculated as if the variables involved were

[4] For further insight, see Greene (2012) and Cappellari and Jenkins (2003)

continuous variables, based on the idea that the values of both variables are respectively determined by latent continuous variables (Uebersax, 2006). A positive coefficient suggests that investment in the Chinese machines and Kenyan machines are complementary.

The above test is also a test for exogeneity of all the dependent variables, thus, serving as robustness check on the logit models. Thus, although complementarity between investment in Chinese and Kenyan machines is of the most concern in this section, I use the same approach to diagnose the exogeneity and the extent of substitutability (negative complementarity) between investment in Kenyan machines and advanced country machines and between advanced country machines and Chinese machines.

Tables 8 and 9 reports the conditional tetrachoric correlation coefficients for all the three relationships (that is, between China and Kenya, that between Kenya and advanced countries, and that between China and advanced countries). From Table 8, the coefficient for investments in the Chinese and Kenyan machines (0.025) is positive suggesting that they are complementary which support argument made earlier. However, the coefficient reported for investments in Chinese and Kenyan machines in the multivariate model, which controls for the influence of investment in advanced country machines, is negative (-0.027). It is important to note that the coeffients from the two models are both insignificant (even at 10%), suggesting that any complementarity between investments in Chinese and Kenyan machines is not strong and these two variables are exogeneous to each other. The reason why this complementarity appears weak in the data may stem from the existence of a market based cooperation and specialisation with regards to investment in machines in the informal sector. For example, a firm that has invested in a Kenyan lathe machine may not invest in a planer but buy the services of another firm with Chinese planer, in which case the investment in these two machines are complementary but with across-firm effect. That is, complementarity between the Chinese and Kenyan machines does not happen only at the firm level as captured by the quantitative data but also across firms. The following statement from an informal sector operate provides more insight:

> … we here we cannot afford all the machines, so we share the machines we have with other people. You cannot purchase all the machines, they are very expensive and as per our production rate…even the one machine [planer from China] I have I cannot dwell on it all by myself. People bring their timber so I can plane for them to get money to do servicing [maintenance] and pay my rent … (Field interviews, 2013)

Further quantitative data may therefore be needed to test the degree of complementarity across firms. However, my conjecture (based on the qualitative data provided above) is that the across-firm complementarity will be positive and high so that the total complementarity may be positive and perhaps statistically significant.

The results further show that the tetrachoric correlation coefficient for investment in Kenyan and advanced country machines is negative but also insignificant at 10% for both the bivariate and multivariate models. Similarly, the conditional tetrachoric coefficient for investment in Chinese and advanced country machines is also negative and insignicant at 10% for the bivariate model and 5% for the multivariate model. The test for the joint exogeneity of the three dependent variables in the multivariate model shows insignificant relationship, even at 10% significance level. That is, the dependent variables are jointly exogeneous in statistical terms suggesting that overall there is a weak association between investment in the advanced country, Chinese and Kenyan machines.

The above results indicate that it may be less likely that a firm will substitute advanced country machines for Chinese or Kenyan machines. The implication is that though the informal sector firms hope to move away from Kenyan and Chinese machines to the high quality advanced country machines, the firms on average may not be able to achieve this. Such a stalemate may bolster investment in Kenyan and Chinese machines of the type described in this study and may reinforce the complementarity between Chinese machines and Kenyan machines, *ceteris parabus*. Or at best, investment in advanced country machines may occur in tandem with investment in machines from China, Kenya and probably other sources such as India and other emerging economies. Thus, they may not be able to completely move away from the Chinese and Kenyan machines. The caveat however is that this prediction is based on cross sectional data while the relationship between the firms' adoption of the different technologies is largely dynamic, hence, a panel data may produce a more robust prediction. Moreover, like the complementarity, the substitutability may also have across-firm effect.

6. Conclusion

The data in Figure 2 shows that the penetration of the Chinese technology is relatively high in the informal sector compared to the formal sector (over two times higher than the formal sector). Moreover, the Kenyan machines are also popular, even more than the Chinese machines particularly for the informal sector firms while the formal sector firms mainly rely on advanced country machines. A major explanation for this pattern of penetration is the fact that the acquisition cost of the advanced country machines is much higher than the Chinese and Kenyan machines. Many of the firms particularly the informal sector ones that cannot afford the advanced country machines therefore start with the Kenyan and Chinese machines. Hence, the Chinese and Kenyan machines serve as a mode of entry for the firms or they have helped to lessen the effect of high capital cost as an entry and mobility barrier for the firms.

The relationship between the decision to adopt the technologies from the different sources and the characteristics of the firms particularly the age of the firms confirms the entry mode role played by the Chinese and Kenyan technologies. The age of the firms has been found to exhibit a nonlinear effect on the probability of a firm adopting technologies from the three sources. Increases in a firm's age initially increases the probability of investing in Chinese and Kenyan machines but the probabilities decrease after a given age (4.5 years for China and 7 years for Kenya). The reverse relationship is true for advanced country machines, of which the optimum occurs at age 5. The major implication is that the Chinese and Kenyan technologies have improved access to machines by new firms particularly those in the informal sector or enhanced existing firms' access to automation. The effect is more crucial for poor entrepreneurs who would like to start and grow their own businesses rather than to look for wage employment in the formal sector. Also worth noting is the likely complementarity between the adoption of machines from China and Kenya. Thus, these two technologies seem to reinforce each other role in removing the entry barrier. Lastly, the Chinese machines tend to serve more as an entry mode than do the Kenyan machines.

The implication is that in terms of barriers to entry with respect to the high cost of capital, the Chinese technology appears to be more appropriate for operating conditions in developing countries than the advanced country technology. This is particularly true when we consider high cost of capital not only in terms of the absolute magnitude of the investment required but also in terms of the high interest cost of borrowing from financial institutions in developing countries. The high interest cost and generally limited access of firms to bank loans particularly for informal sector firms could be one of the major reasons why the firms tend to rely on internal funds for investment in machines.

The verdict between the Chinese and Kenyan technologies in term of appropriateness appears indeterminate. Both possess characteristics that suit specific aspect of the operating conditions in Kenya. They are both cheap, but Kenyan machines are tailored to meet the scale requirement of the firms while the Chinese machines are superior in term of precision of the machines' functions. The Chinese machines are also amenable for modification or re-engineering to meet the scale requirement.

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APPENDIX

Measuring access to finance using principal component analysis

Principal component analysis (PCA) is a nonparametric statistical tool which can be used to create an index to represent an unobservable variable (a variable that is not directly measurable) from a set of observed variables (Shlens, 2009; Wall, 2006; Cahill and Sanchez, 2001; Ram, 1982). In order to use PCA to create a variable for firms' access to finance, the firms were asked to answer six questions, of which each gives some indication about the firms' level of access to finance from financial institutions including micro finance ones:

a. Does your firm have a bank account or save with a micro finance institution?
b. How many of such accounts does your firm have?
c. Have you applied for loan for your business in the last two years?
d. Have you received any loan for your business from a bank or micro finance institution in the last two years?
e. How many times in the last two years have you received such loans?
f. On a scale of 1-7 (where 1 means no access to finance and 7 means very high access to finance), how do you rate your access to finance?

Table 3 shows the results of PCA indicating the first component explains 68% of the variance in the data with an eigenvalue of 4.084. Kaiser-Meyer Olkin (KMO) test is applied to examine the robustness and sampling adequacy of the PCA performed on the data, which produces an overall correlation of 0.812 shown in Table 4. The rule is that if the KMO is more than 0.5 then PCA analysis can be performed on the data to create the desirable index and this rule is satisfied by the data.

Table 3: Results of principal component analysis

Number of obs.	131
Number of comp.	6
Trace	6
Rho	1.000

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	4.084	3.001	0.681	0.681
Comp2	1.083	0.684	0.181	0.861
Comp3	0.399	0.208	0.066	0.928
Comp4	0.191	0.059	0.032	0.959
Comp5	0.131	0.019	0.022	0.981
Comp6	0.112		0.019	1.000

Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Unexplained
q13a	0.355	0.602	-0.006	0.677	-0.115	0.201	0
q13b	0.422	0.357	0.311	-0.620	0.2138	0.410	0
q13c	0.417	-0.276	-0.640	0.080	0.565	0.122	0
q13d	0.423	-0.407	-0.149	-0.075	-0.733	0.301	0
q13e	0.364	-0.475	0.679	0.318	0.251	-0.126	0
q13f	0.460	0.209	-0.101	-0.209	-0.145	-0.819	0

Table 4: Test for sampling adequacy of the PCA

Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy

Variable	KMO
q13a	0.802
q13b	0.831
q13c	0.829
q13d	0.765
q13e	0.820
q13f	0.827
Overall	0.812

Table 5: Regression results for sequential logit models

	Heavy machines		China		Kenya		Advanced countries	
INDEPENDENT VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agelog	0.223	1.742	1.342*	1.222*	3.001**	3.973***	-2.285**	-2.937*
	(0.431)	(1.142)	(0.709)	(0.725)	(1.323)	(1.151)	(0.970)	(1.729)
Agelog2	0.108	-0.502	-0.353**	-0.406*	-0.832***	-1.027***	0.852***	0.925*
	(0.109)	(0.323)	(0.171)	(0.218)	(0.285)	(0.288)	(0.230)	(0.502)
Kisumu		-1.140*		2.488***		-2.548**		1.642
		(0.659)		(0.940)		(1.032)		(1.025)
Firmsize		0.207*		-0.00174		0.00858		0.0328
		(0.109)		(0.00971)		(0.00960)		(0.0444)
Acc_Fin		0.750***		-0.0606		-0.0853		0.180
		(0.189)		(0.138)		(0.153)		(0.213)
Sole		-0.783		-0.0773		1.373*		-3.170***
		(0.694)		(0.566)		(0.719)		(0.804)
Female		1.155						
		(1.309)						
log_dage		2.434**						
		(1.160)						
above_basic_sch		0.565		-0.0502		-0.194		1.303
		(0.486)		(0.540)		(0.692)		(0.894)
No_bus_card		2.967***		-2.276**		2.208**		-1.887
		(0.805)		(0.917)		(0.996)		(1.292)
Constant	-0.594	-10.88**	-1.911**		-1.303	-3.455**	-0.656	1.698
	(0.488)	(4.330)	(0.766)		(1.425)	(1.416)	(1.107)	(1.892)
Pseudo R-square	0.0585	0.3724	0.0255	0.1807	0.1611	0.2847	0.279	0.5729
Observations	131	131	80	80	80	80	80	80

Note: (1) Robust standard errors in parentheses (2) *** p<0.01, ** p<0.05, * p<0.1

Figure 4: Probability of adoption by the log of firms age

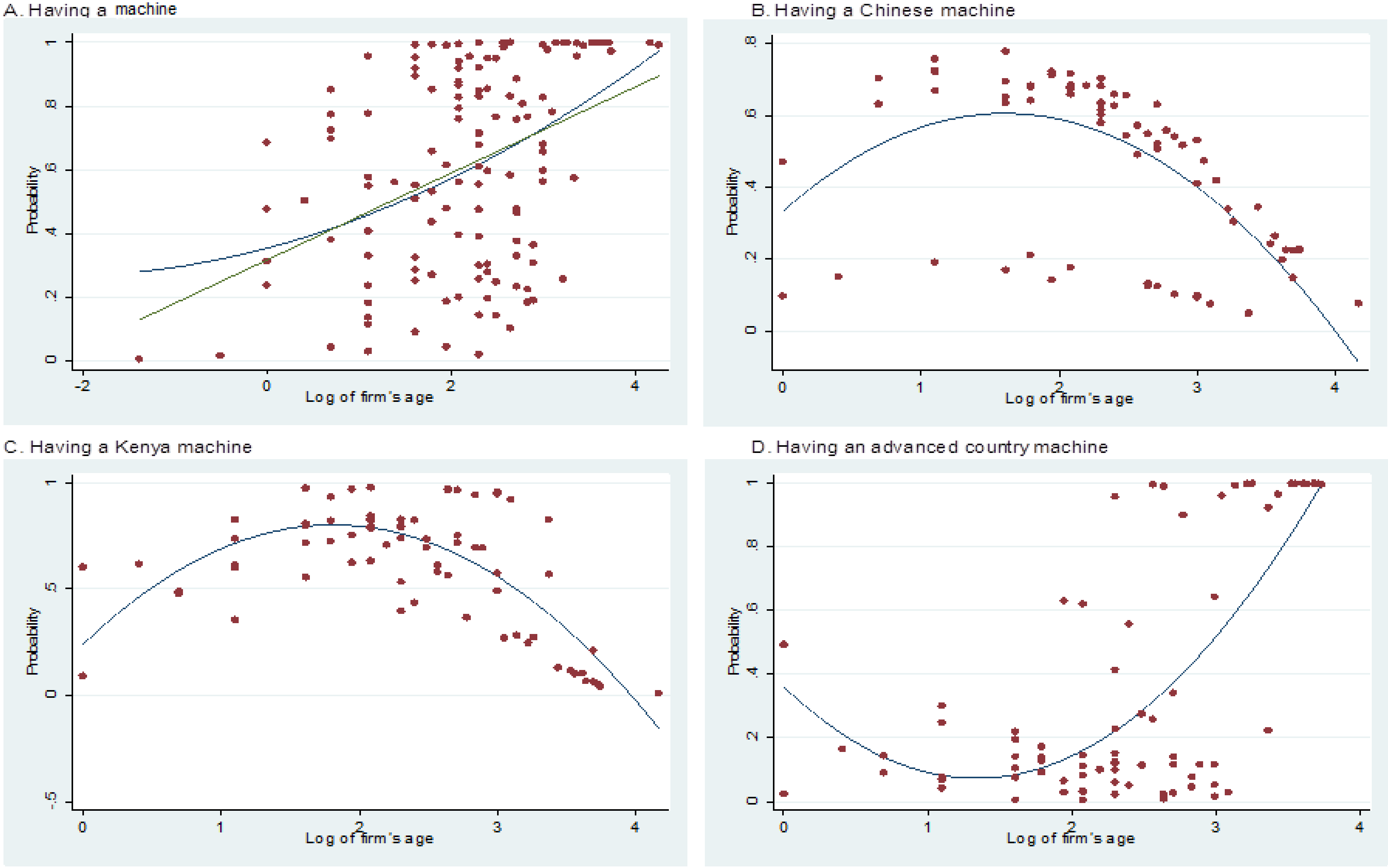

Table 6: Correlation coefficients

	Agelog	Kisumu	Firmsize	Acc_Fin	Sole	Female	log_dage	above_basi	No_bus_ca	informality
Agelog	1									
Kisumu	-0.039	1								
Firmsize	0.418	-0.214	1							
Acc_Fin	0.235	-0.157	0.502	1						
Sole	-0.274	0.052	-0.497	-0.185	1					
Female	-0.210	0.019	-0.006	-0.105	0.074	1				
log_dage	0.529	-0.137	0.456	0.213	-0.316	0.073	1			
above_basic_sch	-0.001	-0.232	0.262	0.313	-0.074	0.047	0.152	1		
No_bus_card	-0.044	0.661	-0.333	-0.293	0.106	-0.003	-0.262	-0.261	1	
informality	0.502	-0.246	0.758	0.411	-0.677	-0.007	0.561	0.246	-0.373	1

Table 7: Summary descriptive statistics

Variables	Ngong	Gikomba	Kibuye	Formal (Industrial area)
Firm age (average)	7.8	12	10.3	31.4
Firm size (average no. of employees)	5.3	1.3	2	66.8
City:				
Nairobi	53	25		20
Kisumu			33	
Ownership (% of firms):				
Partnership	7.6	16	24.2	30
Family owned	0	4	0	70
Sole proprietorship	92.5	80	75.8	0
Total	100	100	100	100
Not having a business card (frequencies)	1	23	33	0
Education (frequencies):				
Primary or basic	17	12	19	2
High school	17	11	11	6
Basic +poly	3	2	2	0
High school +poly	11	0	1	3
University	5	0	0	9
Total	53	25	33	20
Age of operators (average)	38	37	38	58
Sex:				
Male	50	24	31	19
Female	3	1	2	1

Table 8: Results of bivariate probit models and tetrachoric (rho) correlation

INDEPENDENT VARIABLES	China and Kenya				China and Adv. countries				Kenya and Adv. Countries			
	(1)		(2)		(3)		(4)		(5)		(6)	
	China	Kenya	China	Kenya	China	Adv. Countries	China	Adv. Countries	Kenya	Adv. Countries	Kenya	Adv. Countries
Agelog	0.924	1.782**	0.708	2.411***	0.927*	-1.409**	0.700	-1.800	1.780***	-1.477**	2.401***	-1.707*
	(0.562)	(0.699)	(0.444)	(0.672)	(0.555)	(0.617)	(0.437)	(1.101)	(0.673)	(0.623)	(0.660)	(1.031)
Agelog2	-0.293**	-0.501***	-0.233*	-0.628***	-0.294**	0.518***	-0.231*	0.573*	-0.500***	0.540***	-0.625***	0.535*
	(0.128)	(0.152)	(0.129)	(0.166)	(0.128)	(0.141)	(0.128)	(0.299)	(0.148)	(0.146)	(0.164)	(0.277)
Kisumu			1.462***	-1.521***			1.445***	0.924			-1.533***	0.970*
			(0.526)	(0.552)			(0.528)	(0.566)			(0.558)	(0.565)
Firmsize			-0.00187	0.00509			-0.00190	0.0169			0.00504	0.0158
			(0.00558)	(0.00579)			(0.00565)	(0.0253)			(0.00576)	(0.0228)
Acc_Fin			-0.0311	-0.0514			-0.0303	0.0940			-0.0514	0.0958
			(0.0808)	(0.0920)			(0.0802)	(0.0919)			(0.0924)	(0.0932)
Sole			-0.0490	0.808*			-0.0462	-1.842***			0.807*	-1.821***
			(0.344)	(0.413)			(0.339)	(0.463)			(0.414)	(0.462)
above_basic_sch			-0.0100	-0.0914			-0.00525	0.784*			-0.0875	0.782*
			(0.324)	(0.391)			(0.321)	(0.421)			(0.390)	(0.437)
No_bus_card			-1.309***	1.311**			-1.289**	-1.098*			1.319**	-1.167*
			(0.500)	(0.515)			(0.502)	(0.641)			(0.525)	(0.653)
Constant	-0.435	-0.729		-2.073***	-0.433	-0.317		1.030	-0.730	-0.279	-2.062***	1.002
	(0.612)	(0.759)		(0.804)	(0.599)	(0.691)		(1.207)	(0.718)	(0.687)	(0.793)	(1.130)
rho	-0.1262214		0.0254766		-0.0113023		-0.2062326		-0.4278474		-0.1806312	
LR test [Chi2(1)] for rho	0.422161		0.014605		0.002936		0.637676		4.10598		0.428391	
P-value for Chi2	0.5159		0.9038		0.9568		0.4246		0.0427		0.5128	
Observations	80	80	80	80	80	80	80	80	80	80	80	80

Note: (1) Robust standard errors in parentheses (2) *** p<0.01, ** p<0.05, * p<0.1

Table 9: Multivariate probit regression results and tetrachoric (rho) correlation

INDEPENDENT VARIABLES	China (1)	Kenya (2)	Adv. Countries (3)
Agelog	0.689	2.363***	-1.984**
	(0.434)	(0.586)	(1.004)
Agelog2	-0.230*	-0.618***	0.628**
	(0.128)	(0.151)	(0.277)
Kisumu	1.394***	-1.569***	0.964*
	(0.518)	(0.557)	(0.508)
Firmsize	-0.002	0.005	0.012
	(0.006)	(0.006)	(0.014)
Acc_Fin	-0.032	-0.056	0.205
	(0.083)	(0.091)	(0.136)
Sole	-0.045	0.808*	-1.940***
	(0.340)	(0.413)	(0.478)
above_basic_sch	0.004	-0.054	0.668*
	(0.321)	(0.383)	(0.363)
No_bus_card	-1.262**	1.333**	-1.166*
	(0.489)	(0.520)	(0.623)
Constant		-2.019***	1.369
		(0.728)	(1.111)
Observations	80	80	80
rho21_China&Kenya	-0.027		
	(0.180)		
rho31_China&Adv	-0.355*		
	(0.192)		
rho32_Kenya&Adv	-0.409		
	(0.299)		
LR Test (Ho:rho21=rho31=rho32=0)	Chi2	3.637	
	P-value	0.303	

Note: (1) Robust standard error in parentheses (2) ***p<0.01, **p<0.05 and *p<0.1