Industrial Clusters and Social Networks and their Impact on the Performance of Micro- and Small-Scale Enterprises

Evidence from the Handloom Sector in Ethiopia

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I dedicate this thesis
to my parents.

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ABSTRACT

This study empirically investigates how clustering and social networks affect the performance of micro- and small-scale enterprises by looking at the evidence from Ethiopia. By contrasting the performance of clustered micro enterprises with that of dispersed ones, it was first shown that clustering significantly increases profit. The increase in profit from clustering is found to be higher in urban than rural areas. It is also found that regional specific factors determining clustering of micro enterprises are different in urban and rural areas. Second, it is empirically shown that clustering eases the financial constraints of micro enterprises by lowering the capital entry barrier through the reduction of the initial investment required to start a business. This effect is significantly larger for enterprises investing in districts with high capital market inefficiency. Third, the impact of clustering on the entry and exit decisions of farm households into and from non-farm enterprises is examined. Clustering significantly increases the likelihood of entry and enhances the survival of rural enterprises. The impact of entry and exit on household's well-being is further investigated. Entry into non-farm enterprises significantly increases household's income and boosts their food security status, while exit from non-farm enterprises is found to significantly reduce household's income. Finally, the role of ethnic ties on the performance of micro enterprises is investigated. The empirical results show that ethnic ties affect the performance of producers negatively, which implies that the positive effect of ethnic ties, through the reduction of transaction costs arising from market imperfections, does not outweigh the negative effects of closed social networks.

Keywords: clustering, micro enterprises, industrialization, finance, entry, exit, well-being, ethnic ties, transaction cost, Africa, Ethiopia.

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CHAPTER 1

Introduction

1.1 Background

The private sector is often listed as a key driving force for industrialization in Africa in the development literature. A critically important role is played by micro- and small-scale enterprises (MSEs), which constitute the lion's share of the private sector in Africa. MSEs account for more than 90% of all firms outside of the agricultural sector and 50-60% of the off-farm employment in Africa (Yoshino, 2011). With this regard, promoting entrepreneurship in MSEs and stimulating their growth is viewed as a key instrument in poverty reduction efforts both by development agencies and policymakers.

Despite their large employment contribution, MSEs are characterized by low productivity and constitute an insignificant share of the commercial output in most African economies (Yoshino, 2011). MSEs often operate in the informal part of the economy and they do that side by side with a small number of very large firms that are mostly foreign owned, capital intensive and have better access to geographically wider markets (Bigsten and Söderbom, 2006).[1] The dualistic nature of the private sector in Africa is an indication of the "missing middle", where we do not often see MSEs gradually growing into middle size firms and eventually larger ones.

Lack of market integration is often mentioned as one of the reasons as to why the performance of MSEs has remained poor in many African countries (Loening and Mikael,

[1] According to the World Bank Enterprise Survey (WBES) on 17 African countries, large firms are defined as enterprises that Employ more than 100 workers, while small firms are those employing less than 10 workers.

2009; Rijkers et al., 2010). The World Development Report characterizes the private sector in Africa as being in a 'proximity trap', which is manifested through weak agglomeration forces and high transportation costs (World Bank, 2009a). This can result in loss of external scale economies that could hinder firms from gaining "sufficient scale to work efficiently" (Collier and Venables, 2008). Such loss is particularly important for MSEs in Africa that generally operate in thin, fragmented and uncompetitive local markets compared to large firms (World Bank, 2009a). Lack of market integration due to low firm density and long distances to markets also results in high transaction costs, which could undermine MSEs' capacity to take advantage of trade and investment opportunities (Yoshino, 2011). Market failures and the absence of effective institutions to mitigate market failures can further increase the transaction cost of doing business for MSEs in Africa (Tyler and Shah, 2006). The major challenge for MSEs is therefore, to increase their performance by means of improved market integration.

One mechanism that can enhance market integration is the geographic concentration of economic activities (Fujita and Thisse, 1996; Krugman, 1991; 1998). An industrial cluster, which is the geographic concentration of economic activities within a certain sector producing similar and closely related goods, typically leads to a large market that enables small firms to operate at a larger economies of scale arising from the division of labor with in a cluster (Schmitz and Nadvi, 1999; Sonobe and Otsuka, 2006a). Taybout (2000) indicated that the scale at which firms operate in is determined by the market size, whereby low level of economic density may lead to small demand and localized production. Industrial clusters further promote division of labor between small and specialized firms that help to raise collective innovation potential and inter-firm cooperation, fostering learning and innovative advantages (Amin and Thrift, 1994). Moreover, MSEs in industrial clusters may benefit from thick market externalities for specialized inputs (Glaeser et al., 1992), which can affect their investment decisions and choices for factors of production. Besides increasing the internal economies of scale, geographic proximity could therefore result in external economies of scale that can generally lower costs of doing business (Harrison,1992).

In recent literatures, industrial clusters are also noted in helping to ease both the starting and working capital constraints of MSEs in the absence of a well-functioning capital market (Banerjee and Munshi, 2004; Huang et al., 2008; Long and Zhang, 2011). Industrial clusters can help facilitate access to both formal and informal finances and trade credit through repeated interactions between local producers and traders that promote trust, thereby reducing the problem of moral hazard and the cost of monitoring in credit relationships (Grabher, 1993; Schmitz, 1995; Nadvi, 1999; Russo and Rossi, 2001). Collaborative networks within clusters may also reinforce mutually beneficial relationships such as cooperation, allowing access to cheaper credit or the joint purchase of materials at lower prices (Banerjee and Munshi, 2004). The specialization and division of labor in industrial clusters can also ease the financial constraints of MSEs by lowering the capital requirement to invest in the different steps of production (Ruan and Zhang, 2009).

The availability of specialized inputs, local markets and customers within clusters can lower the barriers to start a business compared to dispersed locations (Porter, 2000). Established relationships and social networks with various agents in the same community and the presence of successful local firms can also reduce the “perceived risk of entry” (Porter, 2000). Even after establishment, the presence of a strong cluster environment that fosters growth and enhances regional comparative advantage plays an important role for the survival of enterprises (Schmitz,1995; Schmitz and Nadvi, 1999). Industrial clusters could therefore increase the competitiveness of MSEs and thus impact their performance by helping smooth out market failures and reduce transaction costs. However, the ease of entry into industrial clusters could result in congestion that leads to diseconomies of scale due to fierce competition for limited resources and markets (Sonobe and Otsuka, 2006a).

Even in the absence of geographic proximity, social proximity often manifested through local group cohesion and common identity such as ethnic ties is also another mechanism that can improve market integration (Tyler and Shah, 2006; Yoshino, 2011). In situations where market imperfections prevail, social networks with different agents such as producers and traders may help facilitate trust and can positively impact business outcomes by reducing transactions costs and providing access to various resources (Alesina and La Ferrara, 2005). Firms having close social networks with different agents are well placed to have better information about markets and access to credit (Fisman, 2001). Social networks may also lower the operating cost of the firm by facilitating contractual relationships and reducing the search and reach costs among different agents (Fafchamps, 2002). Although social networks can positively impact business outcomes by reducing transaction costs, they may also hinder economic performance by limiting access to a wider range of business-related ideas and constrain the ability of producers to respond to 'exogenous developments' (Grabher, 1993; Annen, 2001).

While the advantages associated with geographic concentration of economic activities has gained a wider attention in the literature, much of previous researches on industrial clusters have evolved around large-scale enterprises operating in large metropolitan regions where markets are relatively well integrated, competitive and technologically advanced. For example, the advantages of clustering are empirically demonstrated by looking at the effect on the performance of large firms in terms of increasing productivity (Lall et al., 2003), promoting innovation (Oerlemans et al., 2001), and enhancing market linkage to export markets (Bair and Gereffic, 2001). The benefits of clustering are also empirically demonstrated in various success stories like electronics, multimedia, and cultural products agglomerations in California (Scott, 1996), the technology-intensive industrial regions in Baden-Württemberg, Germany (Sabel et al., 1989; Herrigel, 1993) and machine tools networks in Northern and Central Italy (Paniccia, 1998). The potential advantages of industrial clusters for MSEs that operate in fragmented and uncompetitive markets such as in Africa is little studied. The few studies available in Africa focus on case studies, often lacking a comparative analysis. For an overview of studies on clusters in Africa, see Banji and McCormick (2007), Zeng, (2008) and Yoshino (2011). The positive external economies of scale within industrial clusters and their potential economic gains for MSEs in comparison to those operating in less concentrated or dispersed locations is therefore not fully examined. In addition, although considerable efforts have been made to document the existence of spatial concentration of MSEs in Africa, there is not much effort to empirically investigate how that affects their performance using rigorous econometric tools. The few exceptions are, for example, the study by Akoten et al., (2006) on the shoe cluster in Addis Ababa, Ethiopia and Akoten and Otsuka, (2007) on a garment cluster in Nairobi, Kenya. Moreover, an empirical investigation on the role and impact of social networks on MSEs in Africa is very scanty due to limited data on detailed social inter-relationships among different agents (Fafchamps and Minten, 1999; Fafchamps, 2002; Tyler and Shah, 2006).

1.2 Objectives

The general objective of this study is to empirically investigate how clustering and social networks affect the performance of MSEs in Africa by looking at the evidence from the handloom sector in Ethiopia. Ethiopia provides a relevant context to address this objective due to the co-existence of clustered and non-clustered or dispersed MSEs both in urban and rural areas. Besides, the availability of large scale surveys conducted by the Central Statistical Agency of Ethiopia (CSAE), the World Bank and the International Food Policy Research Institute (IFPRI) allow us to implement a detailed counter factual investigation between clustered and dispersed MSEs and look at the impact of clustering and social-networks on their performance.

As in the case for many African countries, MSEs in Ethiopia have a substantial coverage in the private sector. Increasing landlessness and declining absorptive capacity of the agricultural sector for the increased labor force in Ethiopia together with limited growth in employment in the public sector has resulted in a substantial number of new job seekers to turn to MSEs as the main source of livelihood. According to an estimate by the Ministry of Trade and Industry in 2004, the number of people earning their livelihood from MSEs in Ethiopia was eight times larger than those engaged in medium and large scale industrial establishments (MOTI, 2004).

A recent study highlights market fragmentation as one of the major constraints that MSEs face in Ethiopia (Rijkers et al., 2010). Market fragmentation, which is more pronounced in rural parts of Ethiopia results in limited local demand and is one of the reasons why MSEs do not invest and grow (ibid). Following the current strategy of Ethiopia that emphasizes on agricultural development led industrialization, there has been a pressing need by the government to enhance market integration by promoting industrial development that encompasses cluster based MSEs. Among the various types of MSEs found in Ethiopia, handicrafts in general and the handloom sector in particular is given emphasis by policy makers due to its huge employment creation and the existence of naturally emerged clusters both in urban and rural areas. The handloom sector supports the lives of more than 227,000 people with 55% of them existing in rural areas and 48.5% are operated by women (CSAE, 2003). In addition to its income and employment creation, the sector has strategic importance in the economic development of the country through its strong linkage with the agricultural sector and a growing demand for its products both domestically and internationally. Despite these enthusiasm, however, the conditions at each isolated MSE are harsh; productivity and income are low, information and technical know-how are poor and they lack capital and market access often producing at best only simple products (Demesse et al., 2005; Zhang et al., 2011).

Specifically, the study intends to address the following objectives:

(i) Investigate clustering advantages by contrasting the performance of clustered micro enterprises, in terms of profit, with that of control groups of dispersed ones both in urban and rural areas. The study also aims to identify factors determining clustering of micro enterprises in urban and rural areas.

(ii) Examine the advantage of clustering in easing the financial constraints of microenterprises.

(iii) Investigate how clustering affects the entry and exit decisions of farm households into and from non-farm enterprises in rural parts of Ethiopia and examine the impact of entry into and exit from non-farm enterprises on household’s wellbeing.

(iv) Identify various socio-economic factors that determine ethnic ties between producers and traders and analyze how these ethnic ties affect the performance of producers.

1.3 Overview

The remainder of the thesis is organized as follows. Chapter 2 addresses the first specific objective outlined above where the performance of micro enterprises is contrasted with that of control groups of dispersed ones. To correct for selection bias that may arise from entrepreneurs' decision to locate their business in a certain location, clustered microenterprises are matched with dispersed ones that have the same observable characteristics except for being clustered by using the non-parametric statistical method of propensity score matching. In addition, this chapter examines various enterprise and regional specific factors that determine the clustering of micro enterprises in rural and urban areas. It uses more than 4000 micro enterprises in four regions of Ethiopia; namely Tigray, Amhara, the Southern Nations Nationalities and Peoples (SNNP) and the capital city Addis Ababa. The main data is the 2002/03 Cottage/Handicraft Manufacturing Survey conducted by the Central Statistical Agency of Ethiopia (CSAE). This is further supplemented by the 2002/03 Welfare Monitoring Survey and the 2002/03 Large and Medium Scale Manufacturing Establishment Survey both conducted by CSAE. Chapter 3 uses the same data set as in Chapter 2 and investigates the role of clustering in easing the financial constraints of MSEs by examining whether clustering lowers the capital barrier to entry. The financial constraints and capital entry barriers of microenterprises in industrial clusters are compared with those investing outside of clusters using parametric econometric tools.

Chapter 4 examines how clustering affects the entry and exit decisions of farm households into and from non-farm enterprises in rural Ethiopia. In addition to the handloom sector, entry and exit decisions of farm households are investigated on other manufacturing sectors as well. Chapter 4 further investigates the impact of entry and exit into and from non-farm enterprises on farm household’s well-being by using total household income, the food security status of a household and the household’s ability to raise enough money in case of emergency, as indicators. The non-parametric statistical method of propensity score matching is used to account for selection bias that may arise from households’ entry and exit decisions into and from non-farm enterprises respectively. More than 2000 rural enterprises from the Amhara region are used in this study. The main data is the 2006/07 Rural Investment Climate Survey conducted by the World Bank together with CSAE.

Chapter 5 analyzes the importance of social networks formed by ethnic ties in trade relationships of small-scale producers using both a non-parametric and a parametric statistical method. It investigates how various socio-economic characteristics of producers lead to ethnic ties with traders and examine how ethic ties affect their performance. The study uses data collected on handloom producers by the International Food Policy Research Institute (IFPRI) in collaboration with the Ethiopian Development Research Institute (EDRI) from March until May 2008. The survey covered 486 handloom producers in nine clusters, three of which are found in the capital city, Addis Ababa, and the rest in the Gamo zone in SNNP.

Finally, chapter 6 provides the main conclusions and a discussion of the research.

CHAPTER 2

Value-added of Cluster Membership for Micro Enterprises of the Handloom Sector in Ethiopia[♣]

Abstract: *By contrasting the performance of clustered micro enterprises with that of dispersed ones in the handloom sector in Ethiopia, this study shows that clustering significantly increases profit. To correct for selection bias, we match clustered and dispersed micro enterprises that share similar observable characteristics except for being clustered both in urban and rural areas. Results show that clustering is more profitable in urban than rural areas. It is also found that regional specific factors determining clustering of micro enterprises are different in urban and rural areas, highlighting the need to focus on local circumstances when formulating policies to promote clusters.*

Keywords: cluster, micro enterprises, propensity score matching, handloom, Africa, Ethiopia

[♣] Paper by Merima Ali and Jack Peerlings, published in *World Development* (2011) 39(3): 363-374.

2.1 Introduction

The question of how to promote the growth potential of micro enterprises in developing countries has dominated the center of policy debates since the 1960s. Micro enterprises are recognized to have potentials to reach out to small and specialized markets and are flexible in allocating resources to changing opportunities. They also generate income and employment in labor intensive sectors engaging the poorest segment of the society, particularly women and unskilled labor (Nadvi and Barrientos, 2004). Yet, micro enterprises encounter various constraints and transaction costs that affect their business environment and undermine their development (Anderson, 1982; Boomgard et al., 1992). They are often characterized by low productivity, poor information access, limited technical know-how and lack capital and market access, mostly serving local markets. In recent years, however, it has been recognized that industrial clusters can reduce much of the transaction costs faced by micro enterprises and help to overcome their growth obstacles (Sonobe and Otsuka, 2006a; Ruan and Zhang, 2009).

The concentration of economic activities within a certain sector producing similar and closely related goods may result in cost reducing economies of scale, location economies, to micro enterprises in the cluster. These location economies help to increase the competitiveness of micro enterprises in a wider market by promoting ‘collective efficiency’ through knowledge diffusion, specialization and social cooperation (Schmitz, 1995; Schmitz and Nadvi, 1999). On the other hand, there could also be increased costs resulting from fierce competition among micro enterprises and congestion that can offset the potential benefits of clustering (Lall et al., 2003).

Industrial clusters in developing countries are particularly common in traditional and labor intensive micro enterprises in rural and poor urban areas. This has attracted the interest of policy makers and development agencies like World Bank, UNIDO and ILO because of the direct impact such kind of clusters will have on poverty. Owing to the existing policy enthusiasm on promoting clusters, it is therefore important to investigate if clustering actually results in significant economic gains to micro enterprises that could positively impact poverty.

Previous studies are unable to address the above issue fully, because of lack of income data and their orientation towards case studies often lacking comparative analysis. The few comparative analyses available, e.g. Visser (1999) and Weijland (1999), do not take into consideration the issue of selection bias. Is good performance explained by factors determining location economies, or do micro enterprises with certain characteristics look out for profitable and productive locations? Recent empirical studies by Baldwin et al. (2006) and Saito et al. (2009) show that more productive firms self-select into larger markets and are more likely to be clustered in areas that are specialized in particular production. This is because the various advantages of bigger markets and spatial concentrations are “systematically more attractive to the more efficient firms” (Baldwin et al., 2006). With a large market size, low productive firms might also exit from a region or location due to high competition, making these regions and locations to comprise of mostly productive firms. Failure to address selection bias may therefore result in over estimating the impact of clustering on micro enterprises. It is also important for policies aiming at promoting clustering to know the extra income that can be generated by isolated micro enterprises if they were to cluster. Furthermore, since the development opportunities and constraints differ in urban and rural areas, it is important to distinguish factors that determine clustering of micro enterprises in these two regions in order to have appropriate tailor-made policies.

The purpose of this study is to investigate clustering advantages by contrasting the performance of clustered micro enterprises, in terms of profit, with that of control groups of dispersed ones in the handloom sector in Ethiopia both in urban and rural areas. To take into account the problem of selection bias, we match clustered micro enterprises with that of dispersed ones that have the same observable characteristics except for being clustered by using a non-parametric statistical method known as propensity score matching (Heckman et al., 1997). To the best of our knowledge this has not been done before. The study also aims to identify factors determining clustering of micro enterprises in urban and rural areas.

The remainder of the paper is organized as follows. Section 2.2 discusses the conceptual approach used in this study. Section 2.3 is a brief overview of the handloom sector in Ethiopia. Section 2.4 presents the methodology and Section 2.5 provides discussion of the data used. Section 2.6 and 2.7 present the empirical model and the results respectively. Section 2.8 provides a general discussion and conclusions.

2.2 Conceptual Approach

An industrial cluster is a sectoral and geographical concentration of similar and related firms that are often linked by commonalities and complementarities (Schmitz and Nadvi, 1999). Martin and Sunley (2003), mention that a cluster consists of two dimensions. One is the *functional* dimension of a cluster that includes the linkages between firms and interconnected agents like specialized input suppliers, output buyers, and associated institutions such as technical and training centers. Such linkages involve cooperation and networking that result in external economies of scale often manifested through social, cultural and institutional features (Schmitz, 1995; Schmitz and Nadvi, 1999). The second dimension is related to *geographical proximity* where economic activities of a certain sector spatially concentrate in order to benefit from external economies of scale, that are an increasing function of the number of nearby firms (Henderson et al., 2001). Geographic proximity promotes social proximity that results in "social embeddedness" which encourages face-to-face interaction and circulation of new information (Harrison, 1992). Furthermore, geographic proximity facilitates inter-firm cooperation, fostering learning and innovation in specialized firms (Grabher, 1993). Although it is important from an empirical stand point to consider both the *functional* and *geographical* dimensions of clusters, due to unavailability of data, this paper is uniquely concerned in addressing the second dimension. Geographic proximity alone does not provide a direct view about the nature and strength of local inter-firm linkages, knowledge spillovers and social networks; however, it provides information about the existence of external economies of scale that can arise from the various linkages between firms and interconnected agents (Martin and Sunley, 2003).

2.3 The Handloom Sector in Ethiopia

Micro enterprises are the main source of employment next to agriculture in Ethiopia (CSAE, 2002). The handloom sector, being one of the most important segments of micro enterprises in the country, supports the lives of more than 227,000 people with 55% of them existing in rural areas and 48.5% are women (CSAE, 2003). Child labor is a common phenomenon in the sector as well, with the number of persons engaged with less than 18 years of age being 13% (ibid).

In addition to its income and employment creation, the sector has strategic importance in the economic development of the country through its strong linkage with the agricultural sector and a growing demand for its products both domestically and internationally (Demesse et al., 2005). In the handloom sector, micro enterprises are cottage industries where most of the labor and capital are provided by the household owning the firm.

Micro enterprises operating in the handloom sector of Ethiopia are found in naturally emerged clusters and dispersed from each other in different regions of the country both in rural and urban areas. There has not been a comprehensive study about handloom sector in Ethiopia that indicates the exact number of clusters in the country and their size in terms of geographic scale and number of enterprises. The only closely studied cluster through UNIDO intervention is the one found in the capital city Addis Ababa where about 20,000 micro enterprises are found clustered in a district called *Gullele* in the northern part of the city (ILO, 2005).

The *Gullele* cluster comprises of weavers most of them coming from the same ethnic group who have migrated from the southern part of the country. The business culture in the cluster is largely based on imitation where the basic knowledge of weaving has been transmitted from generation to generation. The cluster contains the whole value chain of the handloom sector starting from raw material sourcing until the final consumers at the end of the marketing channel. In the cluster, weavers perform both individually having their own looms and usually working in their homes, and collectively being organized in cooperatives working in common sheds. The main products of the cluster can be divided into semi-finished fabrics and finished products. While the semi-finished fabrics are usually channeled to the domestic garment factories for further processing, the finished products are sold both in the domestic and export markets. Traders in the cluster play an active role in linking weavers working in their homes with retailers and shop owners. Traders also travel to rural towns to collect products in bulk and sell them to shops found around the cluster. Outside of Addis Ababa, clustered micro enterprises are also common in bigger regional cities, touristic areas and rural towns.

Because of lack of information on clustering in the handloom sector outside of Addis Ababa, we construct a concentration index at district level to look where micro enterprises are spatially concentrated relative to other manufacturing establishments using data from the Cottage/Handicraft Manufacturing Industry Survey. The formula and variables used to construct the index are discussed in detail in section 2.5.2. In general, micro enterprises are spatially concentrated in Southern Nations Nationalities and People (SNNP), Addis Ababa, Tigray and Amhara in descending order. The four regions alone cover 82% of the total handloom establishments in Ethiopia. In urban areas SNNP followed by Addis Ababa have the largest spatial concentration of micro enterprises while Tigray and Amhara have the largest spatial concentration in rural areas. Particularly in Tigray and Amhara, micro enterprises are concentrated in rural towns and touristic sites. According to the concentration index, we identified 27 clustered districts in the four regions of Tigray, Amhara, SNNP and Addis Ababa. However, these are not the only clusters in the country as the identification of clusters is clearly dependent on the fact that concentration index has been calculated at district level and is based on samples of micro enterprises from the Cottage/Handicraft Manufacturing Industry Survey.

2.4 Propensity Score Matching

In order to capture the impact of clustering on profitability of micro enterprises, the study uses propensity score matching (PSM). The main pillars of PSM are individuals (micro enterprises), the treatment (clustering) and potential outcome (profit). The idea is to match those micro enterprises that receive a treatment (clustered micro enterprises) with that of a control group (dispersed micro enterprises) sharing similar observable characteristics. Then the mean effect of treatment (clustering) is calculated as the average difference in profitability between the treated and non-treated control group.

Let $D_j \epsilon (1,0)$, be an indicator of whether micro enterprise j is clustered or dispersed, that is whether micro enterprise j has received a treatment or not. The potential outcome of clustering, profit, is defined as, $\pi_j \left(D_j\right)$ for each micro enterprise$j$, where $j = 1, \ldots, N$ denoting the total population. The effect of clustering on individual micro enterprise j can then be written as:

$$T_j = \pi_j(1) - \pi_j(0) \quad (1)$$

With this specification, however, one cannot observe the counterfactual, $\pi_j\ (0)$, that is the profitability of enterprise j had it not been located within a cluster. Since the individual treatment effect, T_j cannot be estimated, the average treatment effect from the population should be computed.

Although there are different ways to estimate the average treatment effect, the one that has received most attention in the evaluation literature is the average treatment effect on the treated (T_{ATT}), which is defined as:

$$T_{ATT} = E(T|\ D = 1) = E[\pi(1)|\ D = 1] - E[\pi(0)|\ D = 1] \quad (2)$$

where, T_{ATT} is the average treatment effect on the treated and $E[\pi(1)|\ D=1]$ is the expected outcome for those micro enterprises which are actually clustered or received a treatment and $E[\pi(0)|\ D=1]$ is the counterfactual for the treated which estimates what the outcome would be if those micro enterprises which in fact are clustered become dispersed or do not receive a treatment. Since the counterfactual cannot be observed, it should be constructed using dispersed micro enterprises that share similar observable characteristics, except for being clustered.

An important assumption of this method is the conditional independence assumption (CIA) which states that, the set of observable characteristics should determine both the probability (propensity score) of receiving a treatment (being clustered) and the outcome of interest (profit of micro enterprises); that is $(\pi_0, \pi_1) \perp D|\ v$, denoting the statistical independence of (π_0, π_1) conditional on observable characteristics, v. This is a non-causality condition that excludes the dependence between the potential outcome and the probability of receiving a treatment (Heckman et al., 1997).

If all the variables influencing both the probability of being clustered and profitability of micro enterprises are not incorporated, then CIA is violated since the impact of clustering will be accounted by information that is not included in the estimation of the propensity score (Smith and Todd, 2005). To prevent the violation of CIA, explanatory variables that are supported by economic theory are included in the probit model that is used to generate predicted probabilities (propensity scores) which will then be used to match micro enterprises (see section 2.6.2).

Given that the CIA holds, the PSM estimate for T_{ATT} can be written as:

$$T_{ATT}^{PSM} = E_{P(v)|\ D=1)}\{E[\pi(1)|\ D=1, P(v)] - E[\pi(0)|\ D=1, P(v)]\} \quad (3)$$

where $P(v)$ is the probability of receiving a treatment (being clustered) based on observable characteristics, v.

Once the probit model is estimated to generate the propensity score, a dispersed micro enterprise that is 'closest' in terms of propensity score has to be selected as a match. This is done using the kernel matching method that associates the outcome π of a clustered micro enterprise j with the matched outcome that is given by a kernel-weighted average of all the dispersed micro enterprises. Since the weighted average of all micro enterprises in the dispersed group are used to construct the counterfactual outcome, kernel matching has an advantage of lower variance because more information is used (Heckman et al., 1998). The weight given to dispersed micro enterprise i is in proportion to the closeness between i and the clustered micro enterprise j.

In order to eliminate outliers that have very high and very low propensity scores, the matching is restricted on the area of Common Support in the sample which is defined between the lowest propensity score of the clustered and the highest propensity score of the dispersed group. To be effective, matching should balance observable explanatory variables across clustered and dispersed micro enterprises. For this a balancing test is performed after the match. This test is primarily concerned with the extent to which differences in the observable characteristics between the clustered and dispersed groups have been eliminated so that any difference in outcome variable (profit) between the two groups can be inferred as coming from the treatment i.e. clustering.

2.5 Data

2.5.1 Data Sets

Enterprise level data from the 2002/03 survey on Cottage/Handicraft Manufacturing Industry, conducted by the Central Statistical Authority of Ethiopia (CSAE), is used in this study. The sampling frame for this survey was obtained from the listing of the 2001/02 Population and Housing Census which was conducted by CSAE. The survey covered both urban and rural parts in 11 regions of the country. Taking into account population size and expected distribution of cottage industries, a two stage stratified cluster sample design was used for regional (urban) capitals, major (other) urban cities and rural areas (CSAE, 2003). For another 8 urban centers a three stage stratified cluster sample design was used to select the sample. In each case, sample units were selected systematically using probability proportional to size; size being adjusted to the number of cottage industries obtained from the 2001/02 Population and Housing Census (ibid). In this data set micro enterprise specific variables like gender, age, experience and schooling of the owner operator are incorporated. In addition, value of production, cost of raw materials, wages and salaries for paid non-family workers and other operational costs of the establishment are included. After dropping observations with incomplete or inconsistent information, we were able to obtain a complete data set from a total of 4336 micro enterprises from 120 districts in four different regions of Tigray, Amhara, SNNP and Addis Ababa. 1945 (45%) micro enterprises are from urban areas and the rest 2391 (55%) are from rural areas.

The enterprise level data are supplemented by additional location specific variables from the 2002/03 Welfare Monitoring Survey conducted by CSAE. It contains information regarding markets, transport infrastructure (an all-weather road) and credit (micro finance institution) at each district level. Information from the 2002/03 census survey on Large and Medium Scale Manufacturing Establishments conducted by CSAE is also used. This census incorporates information about large manufacturing establishments of various industries located in different zones (a higher geographic unit next to district).

The financial information from the Cottage/Handicraft Manufacturing Industry Survey is used to calculate profit of micro enterprises. Profit[2] is defined as value of production minus value of raw materials, operational costs and wages and salaries for paid apprentices, seasonal and temporary workers and paid permanent workers. A limitation of financial data obtained from micro enterprises in developing countries in general and Ethiopia in particular is lack of reliable and adequate profit data. In the survey more than 90% of the

[2] Opportunity cost of family labor is not included in this calculation. In the operational costs, water and electricity payments, transportation cost and cost of repair and maintenance are included. The data to calculate profit is obtained from the 2002/03 Cottage/Handicraft Manufacturing Industry Survey.

micro enterprises do not keep financial records which might lead to recall problems during the time of the survey. Inseparability of the business activity from the household, seasonality of production, unwillingness of producers to reveal their earnings, etc. may also lead to unreliable measures of profit (Daniels, 2001; de Mel et al., 2009).

It is important from an empirical points of view to check the reliability of the above measure of profit by comparing it with alternative measures such as those based on self-reported profits by producers (de Mel et al., 2009) and various proxies of profits obtained through more detailed questions and repeated visits (Daniels, 2001). However, due to unavailability of data, our measure of profit is based on financial information obtained from producers from a single-visit survey.

2.5.2 Location Quotient

Since the concept of 'cluster' and 'dispersion' is prone to subjective judgment, several standard global indices have been developed to measure spatial concentration of activities. The location quotient (LQ) is one of the commonly utilized concentration indices (O'Donoghue and Gleave, 2004). It quantifies how "concentrated" a sector is in a certain location compared to a larger geographic area such as a nation, region or sub region, showing the proportion of specialization of a certain sector in a given location.

$$LQ_I = (e_I/e)/(E_I/E), \tag{4}$$

where LQ_I the location quotient of industry I in the local region, e_I employment of industry I in the local region, e total manufacturing employment in the local region, E_I reference area employment in industry I, E total reference area manufacturing employment. Here total manufacturing employment includes employment in micro, medium and large scale manufacturing industries.

The location quotient is based upon calculating the ratio between employment of a certain sector to some reference unit. It is computed at the finest spatial unit possible, the district, both in urban and rural areas taking zone which is a higher geographic region as a reference point. In order to calculate the LQ, data from the survey on Cottage/Handicraft Manufacturing Industry (2002/03) together with the census data from the Large and Medium Scale Manufacturing Establishments survey (2002/03) both collected by CSAE are used.

Looking at the impact of a LQ on profitability of micro enterprises results in selection bias where more profitable producers might select themselves in locating in areas with higher LQ, causing a biased sample with non-random sampling. Biases arising from self-selection make the determination of direction of causation difficult because the dependent variable (profit) and the independent variable (LQ) are simultaneously determined. In situations where an explanatory variable is jointly determined with the dependent variable, OLS regression will typically provide inconsistent estimates because the independent variable becomes endogenous and is correlated with the error term (Greene, 2008). Even though the continuous variable (LQ) may provide richer information, due to lack of a valid instrumental variable to control for endogeneity, the estimation is done using a non-parametric statistical method (PSM). In this method, we classify micro enterprises in to clustered and dispersed ones and investigate the impact of clustering on profit after controlling for observable factors that can affect the location decision of micro enterprises. Those districts with a LQ of greater than one are selected as having clustered micro enterprises and those with LQ of less than one are selected as having dispersed micro enterprises. This resulted in 2187 (50.44%) clustered and 2149 (49.56%) dispersed micro enterprises. A robustness check is also made by increasing the cut-off point of the LQ.

2.6 Empirical Model

2.6.1 Modeling Enterprises' Location Decision

To model where micro enterprises are likely to spatially concentrate (cluster), it is assumed that they choose a certain location based on the expected profitability of being located there. Consider the existence of two spatial choices (i and r), where i indicates an industrial cluster and r indicates another location outside of a cluster, and N micro enterprises ($j = 1, \dots, N$). The profit derived by micro enterprise j if it is located at i is given by:

$$\pi_{j,i} = \beta X_{j,i} + \varepsilon_{j,i} \qquad (5)$$

β is a vector of unknown parameters, $X_{j,i}$ is a vector of explanatory variables and $\varepsilon_{j,i}$ is a random term reflecting random preferences of micro enterprise j and unobserved attributes of location i (Hausman and Wise, 1978).

The profitability of micro enterprise j at i depends, among other things, on net location benefit which is the difference between gross location benefits and location costs. Gross location benefits originate from external economies of scale arising from clustering benefits from co-locating near to other producers and regional benefits. Regional benefits are those that are found outside clusters and depend on the intrinsic features of the site such as the quality of local factors of production, availability of bigger markets, credit and transport infrastructure, etc (Krugman, 1991). Regional factors provide advantages that are available to all producers regardless of industry affiliation through benefits that emanate from overall population and wealth of the location. On the other hand, there could also be location costs resulting from fierce competition among micro enterprises for limited common resources due to congestion. Hence, when the location benefits that pull micro enterprises to a center are greater than the location costs that pull them apart, clustering occurs (Henderson et al., 2001). Regional and clustering benefits, however, are not the only factors affecting profitability of micro enterprises and hence their location decision. Enterprise specific characteristics such as age, schooling and experience of the owner operator might play a role by affecting his/her ability to capitalize on location specific benefits (Combes, et al., 2008 and Wheeler, 2006).

If micro enterprise j is located at location i to maximize profit, then the probability(p) that i is chosen by j is given by:

$$p_{j,i} = p(\pi_{j,i} > \pi_{j,r}) \forall\, r \neq i \qquad (6)$$

where $p_{j,i}$ is the probability that enterprise j is located at i and $\pi_{j,i}$ and $\pi_{j,r}$ denote the profit for micro enterprise j if it is located at location i and r respectively.

If we let $d_{j,i} = 1$ if micro enterprise j is located at i (an industrial cluster) and 0 otherwise, then without loss of generality, we can write a probit model as:

$$p_{j,i}(i = 1 |\ X_{j,i}) = \Phi(\beta X_{j,i}) \qquad (7)$$

where β is a vector of unknown parameters and $X_{j,i}$ is a vector of explanatory variables that capture factors determining the location of micro enterprise j at i and $\Phi(.)$ is a commonly used notion for the standard normal distribution function (Greene, 2008).

2.6.2 Variables and Hypothesis

In order to capture factors affecting the probability of being clustered, variables that can affect the profitability and hence location decision of micro enterprises apart from clustering should be controlled for. Following the above argument, the explanatory variables in the probit regression that is used to generate propensity scores for the matching are divided into enterprises specific and regional specific factors.

Enterprises specific factors

As variables describing the characteristics of micro enterprises, we take gender, age, schooling and experience. Gender is indicated by a dummy (1 when male, 0 when female). It is expected that gender matters as in urban areas male are more active in the handloom sector while in rural areas females are more active (CSAE, 2003).

Schooling is measured in years that range from 0 indicating no formal education until 13 indicating higher education beyond high school. Industrial clusters tend to attract more educated workers or operators with better skills because they are capable of "capitalizing on agglomeration benefits" through their superior information processing ability and search techniques compared to less educated workers (Freedman, 2008; Combes, et al., 2008). The high mobility and entrepreneurial tendencies of young and educated adults also attract them to areas with better access to markets and information (Wheeler, 2006). We would therefore expect an increase in schooling to have a positive effect on the probability of being clustered.

Economic concentration could also be more beneficial for workers whose knowledge and skills have accumulated with age and experience. Such accumulation of knowledge is expected to be lower for relatively younger operators and for new entrants and increases as producers become older and stay in business longer. But once producers have reached a certain level of age and experience, the accumulation of knowledge may decline. For this, we expect the effect of age and experience on the probability of being clustered to be non-linear, therefore we include in the probit regression the squared terms in addition to the level.

Regional specific factors

These are further classified in to concentration of industrial activities and access to various facilities outside clusters.

Concentration

We include three variables describing industry concentration; first, concentration of micro enterprises from other industries other than the handloom sector in the same district, second, concentration of big textile factories in the same zone (group of districts), third, concentration of big manufacturing factories from other industries in the same zone. All three are measured using location quotients based on employment.

These three variables are indicators of externalities that surrounding industrial activities have on the handloom sector (see Krugman, 1991; Fujita et al., 1999). For example, Fujita and Thisse (1996) and Lall et al., (2003) showed that producers benefit from the existence of big firms from the same industry as well as other industries in nearby areas. These inter-industry and intra-industry benefits include information spillovers, technological externalities, availability of pool of skilled workers, and existence of common services such as research and training centers, government and regulatory institutions, banking services etc.

Large urban areas are more diverse and can support a wider range of industrial activities that require buyers and sellers to be in close spatial proximity than rural areas and small cities that specialize in a few activities (Fujita et al., 1999). Because of the larger presence and concentration of manufacturing activities in the urban areas of Ethiopia, we expect micro enterprises to be more likely to cluster around manufacturing industries in urban than in rural areas.

The concentration of big textile factories in the same zone is expected to have a positive effect both in rural and urban areas as there can be backward and forward linkages in terms of inputs sharing and information spillover with regards to design, markets and outputs between big producers and micro enterprises operating in the same industry. For micro enterprises that operate in industries other than the handloom sector and located in the same district, they can have a positive effect if their concentration promotes multiple specializations, which further triggers information spillover. On the other hand there can also be costs due to higher rents for housing and congestion, the latter often resulting in fierce competition for limited common resources.

Access to market, transport infrastructure and credit

Market access is calculated following the gravity model of accessibility (Evenett and Keller, 2002). According to this model, the degree of interconnection between two locations is directly related to the attractiveness of the locations which can be captured by employment opportunities and purchasing power of the population and is indirectly related to the physical separation between the two locations which can be captured by the presence or absence of a transportation link, physical distance or travel time. The general formulation of the gravity model following Hansen (1959) is:

$$A_m = \sum W_n f(d_{mn}) \qquad (8)$$

where, A_m is the accessibility indicator at location m (which in this case is a cluster), W_n the weight that captures the attractiveness of location n (which in this case is a market), $f(d_{mn})$ is the "impediment" function that separates the original location m and destination n as a function of distance d_{mn}. The gravity model imposes a distance decay formulation on the impediment function that takes the inverse power (Lall et al., 2003).

In order to calculate market access, information from the Welfare Monitoring Survey, 2002/03 is used. Due to lack of data on purchasing power of the residents, population within each district is used in order to indicate the size of potential market. For a variable to be used in the impediment function, average travel time to the nearest market place is used. Following the general formulation of the gravity model, market access is then calculated as population in 100,000 divided by hours taken to reach the nearest market place in each district. In order to capture the impact of distance decay, a square of the above specification is used. Economic activities are likely to concentrate around markets because of increasing returns to scale in production due to proximity to consumers and reduced transportation costs while delivering goods to the market (Krugman, 1991), so we expect market access to have a positive effect on the probability of being clustered.

In relation to market access, producers generally are more likely to concentrate in locations where the transport infrastructure enables to reach markets at low costs (Henderson et al., 2001; Krugman, 1998). And hence "activities are pulled *disproportionally*" towards locations with good infrastructure facilities (Henderson et al., 2001). We measure access to transport infrastructure by the average travel time taken to reach the nearest all-weather road at each district level, which is obtained from the Welfare Monitoring Survey 2002/03. Travel time to the nearest all-weather road instead of physical distance in kilometers is chosen to take into account for quality of the infrastructure. Although the availability of high quality infrastructure eases geographic barriers of interaction, enhancing technology diffusion and information spillover (Krugman,1991), it can have an opposite effect as there is more need to cluster when there is poor infrastructure. We would expect this effect to be more pronounced in rural areas due to their remoteness.

Micro enterprises in developing countries in general and Ethiopia in particular struggle with credit constraints, which are one of the key obstacles for their growth (Ageba and Amha, 2006). Availability of credit services that target micro enterprises such as micro finance institutions (MFI) are considered to ease the credit constraints. In this study, average travel time in hours taken to reach the nearest MFI is used to capture the availability of credit services in near-by areas. We would expect micro enterprises to cluster near MFI; hence an increase in average hours to reach MFI would decrease the probability of being clustered.

Additional variables

As two additional variables we include a dummy indicating whether or not an enterprise is located in Addis Ababa and a dummy indicating whether or not an enterprise is located in a rural town. These two dummies are considered relevant since they provide information about all kind of externalities that cities provide.

2.7 Results

2.7.1 Estimation Results of the Probit Regression

The results of the probit regression for factors that determine clustering of micro enterprises are presented in Table 2.1. The predicted probabilities from the probit regression are used to generate matched micro enterprises. Because there is significant differences in many of the explanatory variables used including monthly profit between rural and urban areas (see Table 2.I.1, Appendix 2.I), the analysis has been performed for urban and rural areas separately.

Although some variables (e.g. schooling) increase the probability of being clustered both in rural and urban areas, we find some differences. While micro enterprises that are run by female and younger operators are more likely to cluster in rural areas, this is not the case in urban areas. This confirms the fact that there are more female operators in rural than urban areas (CSAE, 2003). Loening et al., (2008) also found that young females are the main operators of non-farm enterprises in rural Ethiopia.

The concentration of micro enterprises in the same district but operating in other industries has a positive and significant effect in urban areas. This could be because positive externalities from information spillover and multiple specializations outweigh the negative effect of congestion and fierce competition. It is also positive in rural areas although not significant.

Similarly, concentration of big textile factories in the same zone has a positive and significant effect both in urban and rural areas. This points the importance of backward and forward linkages in terms of inputs sharing and information spillover with regards to design, markets and outputs between big textile factories and micro enterprises operating in the same industry. Contrary to what we expected, micro enterprises have low probability of being clustered around big manufacturing industries in urban areas. This is probably because manufacturing industries in urban areas are located in suburbs that are usually located at the outskirts of urban towns often marked by the government as industry or export zones.

Micro enterprises have high probability to cluster around markets in urban areas while they cluster further away from markets in rural areas. This is in line with the finding that micro enterprises in urban areas are more likely to cluster where there is good infrastructure as can be captured by time taken to reach to the nearest all-weather road while they cluster in remote areas where the all-weather road is not accessible in rural areas. This could indicate that there is more need to cluster in rural areas to compensate for remoteness. This finding also confirms Weijland (1999) who stated that industrial clusters are important in remote areas as they help to attract traders that link cottage industries with distant markets. Traders are usually attracted to such clusters because the “trading cost per transaction” is lower when producers are concentrated in one area (ibid). A recent study on rural clusters in the handloom sector in Ethiopia also showed that traders from the capital city Addis Ababa and other urban towns travel to rural areas to collect finished products in bulk from various producers operating in clusters (Ayele et al., 2009). These traders that base their business in towns like Addis Ababa are mostly born and grown in rural areas and have strong social networks and family ties that can enhance trust and help to establish stable transactions (ibid).

Table 2.1 Marginal effects[a] of the probability of being clustered resulting from the probit regressions (standard errors in parentheses).

	Urban	Rural
Male (dummy)	0.23(0.03)***	-0.14 (0.07)**
Age	-0.00(0.01)	-0.01 (0.006)*
Age squared	0.00 (0.00)	0.00 (0.00)
Schooling	0.02 (0.01)***	0.02 (0.01)*
Experience	-0.00 (0.00)	0.00 (0.00)
Experience squared	0.00 (0.00)**	0.00 (0.00)
Concentration of micro enterprises (in same district and different industry)	0.22 (0.04)***	0.02 (0.02)
Concentration of big textile factories (in the same zone)	0.03 (0.01)***	0.07 (0.04)*
Concentration of big manufacturing factories (in the same zone and different industry)	-0.13 (0.02)***	-0.08 (0.06)
Market access	0.004 (0.001)***	-0.05 (0.02)**
Hours to the nearest micro finance institution	0.27 (0.03)***	-0.00 (0.00)
Hours to the nearest all-weather road	-0.43 (0.04)***	0.11 (0.05)**
Addis Ababa (dummy)	0.12 (0.05)***	--
Rural town (dummy)	--	0.72 (0.02)***
Number of observations	1945	2391
Prob > chi^2	0.00	0.00
Count R^2 (correctly classified)[b]	78.35%	73.61%

*significant at 10%, ** significant at 5%; *** significant at 1%

[a] Marginal effects are estimated at the sample mean except for the dummy variables.

[b] Count R^2 is calculated as the ratio of number of correct predictions to total sample. It shows what proportion of the dependent variable is correctly predicted by the model (Green, 2008).

Contrary to what we expected, we find a significant result for urban areas where micro enterprises cluster further away from MFIs. This could be due to the importance of informal finances like borrowing from friends and families in micro enterprises (Steel et al., 1997; Buckley, 1997), which may have played a substitute role to MFI services by easing the constraint on working capital. Furthermore, a current study by Ruan and Zhang (2009) showed that industrial clusters, through intensive division of labor, can help micro enterprises overcome financial constraints by specializing according to their "capital portfolio". Through trust developed with traders and input suppliers, trade credit also helps micro enterprises in industrial clusters to indirectly gain access to working capital (ibid).

Micro enterprises in general are more likely to cluster in the capital city Addis Ababa than in other urban areas and cluster more in rural towns. This implies that micro enterprises are attracted by all kinds of positive externalities that the capital city and rural towns provide. A recent survey conducted by the International Food Policy Research Institute (IFPRI) on handloom producers in Ethiopia showed that micro enterprises in rural areas migrate to electrified towns searching for better infrastructure, which will enable them to work longer hours (Ayele et al., 2009).

2.7.2 Effect of Clustering on Profit

Using the same explanatory variables as in the probit regression, a propensity score matching is done on micro enterprises both in urban and rural areas using Kernel matching[3]. The results of the match are presented in Table 2.2 and 2.3.

The matching is done between micro enterprises from the treated (clustered) and non-treated (dispersed) group that are on the Common Support (see Table 2.3). As shown in Table 2.2, in urban areas, matched clustered micro enterprises have a monthly average profit that is 89.29 birr (10.38 \$)[4] higher than that of matched dispersed micro enterprises.

[3] STATA software on PSMATCH2 is used that is developed by Edwin Leuven and Barbra Sianesi.
[4] The 2003 exchange rate was l \$ = 8.6 birr.

This is equivalent to a 100.4% increase in average monthly profit for micro enterprises due to clustering[5]. Similarly, matched micro enterprises in rural areas have a monthly profit that is 13.52 birr (1.57 $) higher than that of matched dispersed micro enterprises, which is equivalent to a 49.7% increase in average monthly profit due to clustering. It can also be observed from Table 2.2 that matched clustered micro enterprises in rural areas have a lower level of profit than their urban counterparts.

Table 2.2 Average monthly profit in birr for clustered and dispersed micro enterprises using Kernel Matching. The standard errors[a] for the Average Treatment Effect of the Treated ($\boldsymbol{T_{ATT}}$) are in parentheses.

		Clustered (treated)	Dispersed (non-treated)	Difference
Urban	Unmatched	156.43	114.91	41.52
	Matched ($\boldsymbol{T_{ATT}}$)	178.26	88.96	89.29 (16.39)***
Rural	Unmatched	55.71	36.17	19.54
	Matched ($\boldsymbol{T_{ATT}}$)	40.74	27.21	13.52 (4.24)***

* significant at 10%, ** significant at 5%; *** significant at 1%.
[a] the standard error for the $T_{ATT}$is computed after bootstrapping 100 times

Table 2.3 Number of micro enterprises with Kernel Matching on the Common Support

		Clustered (treated)	Dispersed (non-treated)	Total
Urban	On support	183	931	1114
	Off support	831	0	831
	Total	1014	931	1945
Rural	On support	733	1256	1989
	Off support	402	0	402
	Total	1135	1256	2391

To check how the matching has performed in terms of eliminating differences in observable explanatory variables between the matched clustered and dispersed micro enterprises,

[5] The percentage increase in monthly average profit is calculated as the difference in average profit between matched clustered and dispersed micro enterprises divided by average profit of matched dispersed micro enterprises.

balancing tests are undertaken. The ones used in this study are t-tests for equality of means on each explanatory variable between clustered and dispersed micro enterprises before and after the match (Sianesi, 2004) and a chi square test for the joint significance of variables used in the probit model before and after the match (Sianesi, 2004; Smith and Todd, 2005).

For urban areas, all explanatory variables before the match between clustered and dispersed micro enterprises are not balanced, and the equality of means is rejected at the level of 5%, except for variables experience and distance to micro finance institution (Table 2.II.1A in Appendix 2.II). After the match, variables like experience and distance to micro finance institution are not balanced and the equality of means is rejected at 5% significance level. However, the chi square test after the match (Table 2.II.1B in Appendix 2.II) confirms that all the variables in the probit model are not jointly significant with prob>χ^2 = 0.23. This implies that there is no systematic difference in the distribution of explanatory variables between the matched clustered and dispersed micro enterprises.

For rural areas, most of the explanatory variables are not balanced before the match, especially for location specific variables. After the match, however, all the explanatory variables are balanced where equality of means for each variable is accepted at the level of 5% (Table 2.II.2A in Appendix 2.II). The chi square test after the match also confirms that all the variables in the probit model are not jointly significant with prob>χ^2 = 0.13 (Table 2.II.2B in Appendix 2.II). Looking at the balancing test for rural areas further depicts that almost all matched clustered and dispersed micro enterprises are from locations outside rural towns, and this explains why the T_{ATT} for the matched micro enterprises is only 13.52 birr compared to the difference in profitability for the unmatched micro enterprises, which is 19.54 birr.

The overall balancing tests imply that, the matching procedure has produced samples of micro enterprises that can reasonably be regarded as almost similar and any difference in profits between clustered and dispersed micro enterprises can be inferred as coming mainly from the effect of location economies of clustering.

2.7.3 Robustness Check

Since we used a LQ of 1 as a cut-off point to indicate whether a micro enterprise is clustered or not, we perform a robustness check to see if a higher cut-off point will also result in more profit for clustered micro enterprises. For this, we use the average LQ as a cut-off point with LQ of 1.30 and LQ of 1.47 for urban and rural areas respectively. The estimated T_{ATT} are given in Table 2.4 below.

As can be seen from Table 2.4 the extra profit earned by clustered micro enterprises increases as the cut-off point increases. Clustered micro enterprises earn 123.41 birr (14.35 $) and 14.57 birr (1.69 $) more than dispersed micro enterprises in urban and rural areas respectively. This is equivalent to a 147% and 50% increase in average monthly profit due to clustering for urban and rural areas respectively. This implies that highly concentrated micro enterprises earn higher profits.

Table 2.4 Average monthly profit in birr for clustered and dispersed micro enterprises using Kernel Matching. The standard errors[a] for the Average Treatment Effect of the Treated ($\boldsymbol{T_{ATT}}$) are in parentheses.

		Clustered (treated)	Dispersed (non-treated)	Difference
Urban	Unmatched	166.81	113.41	53.40
	Matched (T_{ATT})	207.34	83.93	123.41 (41.69)***
Rural	Unmatched	53.36	35.93	17.43
	Matched (T_{ATT})	43.81	29.24	14.57 (5.79)**

* significant at 10%, ** significant at 5%; *** significant at 1%.
[a] the standard error for the T_{ATT} is computed after bootstrapping 100 times

The balancing test for the match confirms that all the explanatory variables for urban and rural areas are balanced based on a t-test where the means of each variable is not significantly different from each other at the level of 1% at the 95% confidence interval.

Table 2.5 Number of micro enterprises with Kernel Matching on the Common Support

		Clustered (treated)	Dispersed (non-treated)	Total
Urban	On support	172	1102	1274
	Off support	671	0	671
	Total	843	1102	1945
Rural	On support	743	1086	1829
	Off support	562	0	562
	Total	1305	1086	2391

2.7.4 Sensitivity Analyses

In cottage industries, total family income is usually composed of net family income from enterprise work and family income from non-enterprise work[6]. Because different family members are engaged in enterprise and non-enterprise works, there could be a shift of family labor from one activity to the other. For example, due to increased productivity from location economies, micro enterprises operating in clusters might systematically use more family labor than dispersed micro enterprises by shifting family labor engaged in non-enterprise work towards enterprise work. As a result, the net family income from enterprise work (i.e. profit) would be an over estimation of the true impact of clustering because, while the increased earning in micro enterprises operating in clusters could be due to location economies, it could also be driven by the shift of family labor across activities. The profit change we calculated in this paper, which is equivalent to the change in net family income from enterprise work, should therefore be corrected for the amount and cost of family labor used in the enterprises.

Due to lack of data on the number of hours worked by each family member both in the enterprise and non-enterprise activities, we cannot directly correct profit using the amount and cost of family labor. However, we apply two sensitivity analyses that help us capture

[6] Remittance and transfers from government and non-government bodies can also constitute total family income.

the ‘true’ extra profit from clustering, which is not affected by the shift of family labor across activities due to location economies.

The first sensitivity analysis we perform is to compare the profitability of micro enterprises operating inside and outside a cluster using non-enterprise income as one of the control variables in the generation of propensity scores. Matching micro enterprises between these two groups using propensity scores will generate treated and non-treated groups of micro enterprises having the same level of non-enterprise income. That is, the matching will generate non-treated groups of micro enterprises operating outside of a cluster whose non-enterprise income does not change even after they are exposed to the treatment i.e. operating inside a cluster. If the non-enterprise income is the same for the treated and non-treated groups, this allows us to assume that there has not been any substitution of family labor from non-enterprise work to the enterprise work due to clustering. In other words, profit has not been affected by a change in enterprise size due to shift of family labor across activities as a result of clustering. One possible reason why there might not be a change in family labor use even when there is an increase in profitability from clustering could be when all the ‘relevant’ family labor has been absorbed in the enterprise. This could be the case when family members working in the enterprise lack the appropriate education and skills that would give him/her a higher return if he/she works outside the enterprise and vice versa.

The second sensitivity analysis we perform is to estimate the impact of clustering on total family income, which is the sum of family income from enterprise work and family income from non-enterprise work. This allows us to look at the impact of clustering on the overall income of the family and not just one part of it that might be distorted by substitution of family labor between activities.

The results of the first sensitivity analysis are shown in Table 2.6. There is still a significantly higher profit, 54.15 birr (6.29 $) and 9.36 birr (1.09 $), for micro enterprises operating in clusters both in urban and rural areas respectively, although the resulting increase of average profit for the matched micro enterprises is now lower than what was reported in Table 2.2. Indeed it seems that the previous result of profit comparison was an overestimation of the impact of clustering because we did not account for the substitution of labor from non-enterprise to enterprise work. In the balancing test depicted in Table 2.7, the average non-enterprise incomes of the matched treated and non-treated micro enterprises are not significantly different from each other both in urban and rural areas, showing that there is no variation in family labor between the treated and non-treated groups[7].

Table 2.6 Average monthly profit in birr for clustered and dispersed micro enterprises using Kernel Matching. The standard errors[a] for the Average Treatment Effect of the Treated ($\boldsymbol{T_{ATT}}$) are in parentheses.

		Clusteredd (treated)	Dispersed (non-treated)	Difference
Urban	Unmatched	156.43	114.91	41.52
	Matched ($\boldsymbol{T_{ATT}}$)	158.48	104.33	54.15 (25.84)***
Rural	Unmatched	55.71	36.17	19.54
	Matched ($\boldsymbol{T_{ATT}}$)	40.49	31.13	9.36 (4.70)***

* significant at 10%, ** significant at 5%; *** significant at 1%.
[a] the standard error for the $\boldsymbol{T_{ATT}}$ is computed after bootstrapping 100 times

The results of the second sensitivity analysis, the impact of clustering on total family income, are presented in Table 2.8. There is a significantly higher total family income; 70.83 birr (8.24 $) for urban and 8.45 birr (0.98 $) for rural micro enterprises operating in clusters. This is equivalent to a 67.3% and 23.1% increase in average total family income due to clustering for urban and rural areas respectively. These percentage increases are lower than the one reported for the net family income from enterprise work of 100.4% and 49.7% for urban and rural areas respectively. The reason why there is a lower percentage

[7] The balancing test for the other variables also depicts that there is no systematic difference in the distribution of explanatory variables between the matched clustered and dispersed micro enterprises both in urban and rural areas.

increase in total family income could be due to the decline in non-enterprise income as the family substitutes its family labor from non-enterprise work towards enterprise work. The balancing test for the match confirms that there is no systematic difference in the distribution of explanatory variables between the matched clustered and dispersed micro enterprises with prob>χ^2 = 0.16 and prob>χ^2 = 0.14 for urban and rural areas respectively.

Table 2.7 t- test for non-enterprise income between treated (clustered) and non-treated (dispersed) groups before and after the match.

	Sample	Mean Clustered (treated)	Mean Dispersed (non-treated)	t-test p>|t|
Urban	Unmatched	6.18	9.64	0.04
	Matched	7.38	7.18	0.92
Rural	Unmatched	3.90	10.83	0.00
	Matched	3.96	4.97	0.17

Table 2.8 Average monthly profit in birr for clustered and dispersed micro enterprises using Kernel Matching. The standard errors[a] for the Average Treatment Effect of the Treated ($\boldsymbol{T_{ATT}}$) are in parentheses.

		Clustered (treated)	Dispersed (non-treated)	Difference
Urban	Unmatched	162.62	124.55	38.06
	Matched (T_{ATT})	176.11	105.28	70.83 (37.41)**
Rural	Unmatched	59.61	47.01	12.60
	Matched (T_{ATT})	44.97	36.52	8.45 (4.24)**

* significant at 10%, ** significant at 5%; *** significant at 1%.
[a] the standard error for the T_{ATT} is computed after bootstrapping 100 times

2.8 Conclusions and Discussion

In this paper we examine clustering advantages by contrasting the performance of clustered micro enterprises in terms of profit, with that of dispersed ones in the handloom sector in Ethiopia both in urban and rural areas. To take into account for the problem of selection bias, we match clustered micro enterprises with dispersed ones that have the same observable characteristics except for being clustered. We classify these characteristics into enterprise specific and regional specific factors that determine the likelihood that a micro enterprise will cluster in a certain location.

Although some variables (e.g. schooling and concentration of big textile factories) increase the probability of being clustered both in rural and urban areas, there are also some differences. While micro enterprises that are run by female and younger operators are more likely to cluster in rural areas, this is not the case in urban areas. Furthermore, micro enterprises in urban areas are more likely to cluster around markets and where there are good infrastructure while they cluster in remote rural areas further away from markets. The fact that enterprise and regional specific factors determine clustering of micro enterprises in urban and rural areas differently, therefore, calls a need to focus on the existing local circumstances when formulating policies that can promote clustering.

The Kernel matching reveals that the average monthly profits are significantly larger for clustered than non-clustered (dispersed) micro enterprises both in urban and rural areas. This depicts that location economies exist within clusters after controlling for selection bias. The robustness check shows that the more concentrated micro enterprises are, the higher the percentage increase in profit. The sensitivity analyses show that even after accounting for the possible substitution of family labor across enterprise and non-enterprise works, profit and total family income increase with clustering.

We also find that the percentage increase in profit from clustering is higher in urban than rural areas. Apparently urban clusters provide more location economies than rural clusters probably due to better information spillovers in urban clusters that might arise from increased cooperation and joint action among producers in order to meet the requirements of large and sophisticated markets in urban areas.

An interesting finding of this study is that there are micro enterprises that are not clustered but have the same observable characteristics with that of clustered micro enterprises. Whether or not to implement policies to cluster these micro enterprises, and if yes what kind of policies, depends on the explanation of why, given their similar characteristics, they are operating in isolation. One reason why micro enterprises are operating in isolation might be due to entry barriers to operate within clusters. There are many factors that can explain barriers to entry in which discussing these factors is beyond the scope of the current study. However, one important factor is that micro enterprises are cottage industries operating within the household, which cannot afford to rent separate working shops. Besides, the strong social norms and family ties might restrict their move to other locations. Hence it is difficult for them to abandon their current location and join clustered micro enterprises.

As part of its cluster development policies, the government of Ethiopia is building working shops around the cluster in the capital city Addis Ababa that micro enterprises can rent at a low price or rent on credit. We believe that initiatives such as this could allow those micro enterprises working in isolation to easily join clusters.

A possible caveat of the study is that we only use Kernel matching, however, using other matching methods like nearest neighboring matching and radius matching provided similar results. Another caveat is that because of limited data availability we could not include more economic variables like prices in the model and the measurement of profit is based on a single-visit survey that lack alternative measures to check its reliability. Despite these caveats, the analysis provides a flexible way to overcome selection bias in determining the factors behind clustering and its advantages in terms of generating extra profit.

Appendix 2.I Data

Table 2.I.1 Summary statistics of variables and comparison of means between urban and rural areas

Variable	Town	Mean	S.D	Min	Max	p>|t|
Age (years)	Urban	41.14	15.81	14	88	
	Rural	41.91	15.32	13	87	0.09
Schooling (years)	Urban	2.02	3.22	0	13	
	Rural	0.78	1.93	0	13	0.00
Experience (years)	Urban	15.53	12.91	1	72	
	Rural	16.36	13.28	0	78	0.04
Concentration of micro enterprises in same district and different industry (employment)	Urban	0.94	0.36	0	2.05	
	Rural	0.66	0.72	0	6.57	0.00
Concentration of big textile factories in same zone (employment)	Urban	1.30	3.12	0	10.3	
	Rural	0.62	1.57	0	10.1	0.00
Concentration of big manufacturing industries in same zone and different industry (employment)	Urban	1.42	2.03	0	6.21	
	Rural	0.54	0.97	0	6.21	0.00
Market access (population in 100,000 divided by the square of hours to the nearest market place)	Urban	12.79	22.54	0	57.70	
	Rural	2.22	10.83	0	69.12	0.00
Hours to the nearest micro finance institution	Urban	0.36	0.58	0.01	4.02	
	Rural	3.93	3.27	0.23	22.50	0.00
Hours to the nearest all-weather road	Urban	0.30	0.50	0.01	2.39	
	Rural	1.59	1.19	0.02	5.71	0.00
Monthly profit per micro enterprise (birr)	Urban	120.62	239.07	-491.00	4432.00	
	Rural	45.44	93.08	-724.00	985.00	0.00

Appendix 2.II Balancing tests

Table 2.II.1A t-test for each variable before and after the match for urban areas

Variable	Sample	Mean Clustered (treated)	Mean Dispersed (non-treated)	t-test p>|t|
Male (dummy)	Unmatched	0.80	0.41	0.00
	Matched	0.79	0.80	0.73
Age	Unmatched	39.12	43.33	0.00
	Matched	39.05	40.20	0.49
Age squared	Unmatched	1795.80	2102.00	0.00
	Matched	1756.80	1910.80	0.32
Schooling	Unmatched	2.65	1.34	0.00
	Matched	2.47	2.36	0.71
Experience	Unmatched	16.02	14.99	0.08
	Matched	15.33	18.28	0.03
Experience squared	Unmatched	433.54	379.78	0.06
	Matched	377.77	539.12	0.02
Concentration of micro enterprises in same district and different industry	Unmatched	1.09	0.77	0.00
	Matched	1.11	1.08	0.22
Concentration of big textile factories in the same zone	Unmatched	0.32	2.36	0.00
	Matched	0.21	0.20	0.94
Concentration of big manufacturing factories in the same zone and different industry	Unmatched	0.55	2.36	0.00
	Matched	0.32	0.42	0.30
Market access	Unmatched	21.17	3.66	0.00
	Matched	25.08	21.68	0.23
Hours to the nearest micro finance institution	Unmatched	0.37	0.34	0.31
	Matched	0.31	0.51	0.03
Hours to the nearest all-weather road	Unmatched	0.18	0.43	0.00
	Matched	0.15	0.22	0.14
Addis Ababa (dummy)	Unmatched	0.64	0.14	0.00
	Matched	0.74	0.68	0.25

2. II.1B Chi square test for the joint significance of variables for urban areas

Sample	Pseudo R2	LR chi2	p>chi2
Unmatched	0.38	1047.02	0.00
Matched	0.03	16.24	0.23

2.II.2A t-test for each variable before and after the match for rural areas

Variable	Sample	Mean Clustered (treated)	Mean Dispersed (non-treated)	t-test p>|t|
Male (dummy)	Unmatched	0.61	0.66	0.02
	Matched	0.60	0.58	0.54
Age	Unmatched	40.95	42.77	0.00
	Matched	41.00	40.57	0.59
Age squared	Unmatched	1910.70	2063.60	0.00
	Matched	1922.40	1889.70	0.66
Schooling	Unmatched	0.96	0.61	0.00
	Matched	0.75	0.86	0.30
Experience	Unmatched	16.38	167.35	0.95
	Matched	16.46	16.8	0.66
Experience squared	Unmatched	449.19	439.88	0.74
	Matched	465.87	505.01	0.35
Concentration of micro enterprises in same district and different industry	Unmatched	0.58	0.72	0.00
	Matched	0.65	0.72	0.09
Concentration of big textile factories in the same zone	Unmatched	0.77	0.48	0.00
	Matched	0.75	0.83	0.43
Concentration of big manufacturing factories in the same zone and different industry	Unmatched	0.68	0.42	0.00
	Matched	0.49	0.57	0.20
Market access	Unmatched	0.05	4.18	0.00
	Matched	0.07	0.06	0.53
Hours to the nearest micro finance institution	Unmatched	4.22	3.66	0.00
	Matched	4.47	4.56	0.59
Hours to the nearest all-weather road	Unmatched	1.80	1.41	0.00
	Matched	2.01	1.92	0.15
Rural town (dummy)	Unmatched	0.32	0.00	0.00
	Matched	0.00	0.00	.

2. II.2B Chi square test for the joint significance of variables for rural areas

Sample	Pseudo R2	LR chi2	p>chi2
Unmatched	0.29	949.12	0.00
Matched	0.01	17.65	0.13

CHAPTER 3

Clustering as an Organizational Response to Capital Market Inefficiency: Evidence from Handloom Enterprises in Ethiopia[♣]

Abstract: *Microenterprises in developing countries often struggle with financial constraints. The absence of a well-developed capital market has been listed as a key obstacle to industrialization in developing countries in the development literature. In this paper, we show that industrial clusters, through specialization and division of labor can ease the financial constraints of microenterprises even in the absence of a well-functioning capital market. By using data from microenterprises of the handloom sector in four regions of Ethiopia, we find that clustering lowers capital entry barrier by reducing the initial investment required to start a business. This effect is found to be significantly larger for microenterprises investing in districts of high capital market inefficiency, indicating the importance of clustering as an organizational response to a credit constrained environment. The findings highlight the importance of cluster-based industrial activities as an alternative method of propagating industrialization when local conditions do not allow easy access to credit.*

Keywords: clustering, industrialization, finance, microenterprise, Ethiopia

[♣] Paper by Merima Ali, Jack Peerlings and Xiaobo Zhang. The original version of this paper is published in IFPRI discussion paper series, 01045.

3.1 Introduction

Development agencies and policymakers have long stressed the economic importance of microenterprises in developing countries in general and Africa in particularly because of their large number and their contribution to employment. Reports show that micro- and small-scale enterprises constitute the lion's share of the manufacturing activity in Sub-Saharan Africa, accounting for more than 90% of all firms outside of the agricultural sector (OECD, 2004). They are also sources of income and employment in labor intensive sectors, engaging the poorest segment of the society, particularly women and unskilled workers (Nadvi and Barrientos, 2004). Yet, lack of access to finance remains to be a major obstacle to the expansion of microenterprises (Demirgüç-Kunt and Maksimovic 1998; Rajan and Zingales 1998; Ayyagari et al., 2008). Inefficient functioning of capital markets together with collateral requirements that increase the cost of borrowing are mentioned as major causes of microenterprises' limited access to finance (for example, Tybout 1983; Bigsten et al., 2003; Ayyagari et al., 2008). Limited access to finance can affect the investment patterns of microenterprises and aggravate entry barriers, which can be a prime obstacle for industrialization in Africa (Hernández-Trillo et al., 2005; McKenzie and Woodruff 2006, 2008).

In recent literature, industrial clusters are noted as one form of institution that can help ease the financial constraints microenterprises face when both establishing and expanding their business, even in the absence of a well-functioning capital market. Various studies point to the importance of industrial clusters in facilitating access to informal finances where repeated interactions between local producers and traders promote trust that enables reciprocal exchange of information that may reduce the problem of moral hazards and the cost of monitoring in credit relationships (Becattini 1990; Grabher 1993; Schmitz 1995; Nadvi 1999; Russo and Rossi 2001, Ali and Peerlings 2011b). Collaborative networks within clusters may also reinforce mutually beneficial relationships, such as cooperation, allowing access to cheaper credit or the joint purchase of materials at lower prices

(Becattini 1990; Banerjee and Munshi, 2004). Industrial clusters can also ease the financial constraints of microenterprises by affecting the organization of production (Ruan and Zhang 2008, 2009). The production system within clusters promotes specialization and division of labor, thereby lowering the capital requirement to invest in different steps of production. By relying on components manufactured by others, a firm can specialize in its own products, which require relatively lower amounts of capital, rather than organizing the entire production process. Such division of labor can enable small entrepreneurs with limited endowments to invest in and start a business "by focusing on a narrowly defined stage of production" that best suit their capital portfolio even in the absence of a well-functioning capital market (Huang et al., 2008, 414). However, only few studies have empirically shown the role of industrial clusters as an organizational response to financial constraints (Huang et al., 2008; Long and Zhang 2011; Ruan and Zhang 2009). The few studies available focus on the Chinese experience, making it unclear whether the phenomenon exists in other countries, particularly in African countries, where the capital market is likely to be less developed than in China.

The purpose of this study is to investigate the advantage of clustering in easing the financial constraints of microenterprises operating in Africa by looking at evidence from the handloom sector in Ethiopia. Specifically, it investigates whether clustering can lower the capital barrier to entry by reducing the initial capital investment required to start a business. The study looks at more than 1,000 microenterprises of the handloom sector from four regions of Ethiopia operating both in clusters and in isolation. Ethiopia's handloom sector makes a good case for studying the relationship between the capital entry barrier and industrial clusters because the technology is rather simple and entry is not affected by nontechnical barriers, such as those coming from product differentiation, patents over technologies, and control over supply of raw materials. The only major barrier to entry is access to capital.

The remainder of the paper is organized as follows. Section 3.2 briefly reviews the existing literature. Section 3.3 presents a theoretical framework that depicts how clustering can help ease the financial constraints of starting a business in the absence of a well-functioning capital market. Section 3.4 discusses the data source and describes the Ethiopia's handloom sector. Section 3.5 formulates the empirical model, and Section 3.6 presents the empirical results. Section 3.7 is conclusion and discussions.

3.2 Literature Review: Capital Market Inefficiency and Organizational Choice of Production

A number of studies have shown that the level of capital market development is related to the organizational choice of production within firms. Acemoglu et al., (2009) showed both theoretically and empirically that in countries where there is greater capital market development together with higher contracting costs, vertical integration becomes the common production system. With inefficiently functioning capital markets, on the other hand, a more specialized production would prevail. This is due to the advantage of specialization, which allows firms to break down the more complex and integrated production process and concentrate on activities in which they have a comparative advantage in terms of capital endowments (Huang et al., 2008; Ruan and Zhang 2009).

Using historical evidence, Haber (1991) also noted that in the early periods of industrialization (1840–1880), the level of specialization in the cotton textile industry of a number of Latin American countries was significantly higher than it was in the United States, where the capital market was more developed. Following the creation of modern financial intermediaries in the last decades of the 19th century, however, the level of specialization in the Latin American textile industry declined substantially. Similarly, McKenze and Woodruff (2006) found that credit constrained entrepreneurs in Mexico tend to enter into manufacturing enterprises characterized by technologies that can be broken down in to smaller steps. Organizational innovations that allow the production process to be broken down into small steps make it possible for entrepreneurs with limited capital endowment to participate in the production process by reducing the capital entry barrier (Leff, 1978; Hayami et al., 1998).

A high capital entry barrier is often mentioned as one of the possible reasons for the high return to capital found in micro- and small-scale enterprises in developing countries (Udry and Anagol, 2006; Banerjee and Duflo, 2005; de Mel et al., 2008). Such findings are often considered an indication of microentrepreneurs' unexploited potentials, were the financial constraints to be alleviated (Grimm et al., 2009).

However, there are costs involved with specialization, such as coordinating the various producers involved in different steps of production. Stigler (1951) suggested that the benefits of specialization can best occur when there is clustering that helps to economize coordination costs and facilitate transactions through physical and social proximity. Industrial clusters would then replace the "internal economies of scale that had been the basis of large scale production within a single firm . . . by external economies of scale arising from the division of labor between a number of small firms" (Helmsing 1999, 11). Although coordination costs might be generally lower in industrial clusters, the continuing new entry of firms due to low capital entry barrier may result in diseconomies of agglomeration (Sonobe and Otsuka 2006a). These could arise from congestion, which would then lead to fierce competition for limited resources such as land (Lall et al., 2003).

Large body of literature has posited the advantages of clustering in terms of information spill-over, labor pooling, and market linkages (for example; Marshall 1920; Schmitz 1995; Visser 1999; Sonobe and Otsuka 2006a; Ali and Peerlings 2011a). However, very few studies have empirically examined the role of clustering in reducing financial constraints. Using a sample of 140 footwear-producing enterprises in China's Wenzhou province, Huang et al., (2008) show how industrial clusters can best explain the rapid industrialization of that region despite a lack of basic conditions necessary for economic growth. The authors show that clustering, through specialization and division of labor, enabled a large number of small entrepreneurs to enter the industry by helping them overcome the financial constraints in the early stage of industrialization. For the cashmere sweater cluster of northern Zhejiang province in China, Ruan and Zhang (2008) found a positive correlation between the capital barrier to entry and return on capital when the capital market is not well developed. They also conclude that the division of labor in the cashmere sweater cluster helped "tap the entrepreneurial talents that are scattered in rural areas, thus making better use of capital" (Ruan and Zhang 2008, 22).

Using firm-level data from China's industrial census for the years 1995 and 2004, Long and Zhang (2011) show how clustering eases both starting and working capital constraints through two possible mechanisms. One such mechanism is the specialization and division of labor within clusters that allowed a large number of poorly endowed entrepreneurs from rural areas to become part of the industrial process. The second mechanism is the proximity of various agents within clusters who work to facilitate trust-based trade credit, and hence reduce working capital constraints. Using a panel data set, Banerjee and Munshi, (2004) also showed a causal relationship between social ties and the pattern of investment in the knitted garment cluster in the South Indian town of Tirupur. Producers with strong social ties are found to have started their business with almost three times as much fixed capital compared to outsiders, highlighting the importance of community identity when the capital market is not well developed.

The current study differs from previous work in at least two ways. First, it is the first empirical study to look at the relationship between industrial clusters and financial constraints from an African perspective, using handloom producers in Ethiopia as an example. Second, it compares the financial constraints and entry barriers of microenterprises in industrial clusters with those of microenterprises outside of clusters.

3.3 Theoretical Framework: Clustering, Capital Market Inefficiency, and Entry Barriers

In this section, we discuss how clustering could help ease the financial constraints of microenterprises when starting a business by lowering the required start-up capital in the absence of a well-functioning capital market. For the moment, we assume that entrepreneurs can invest only their capital endowment—that is, they cannot obtain credit from the capital market.

Let an entrepreneur with a certain capital endowment plan to start a business. The entrepreneur faces a production function Y that is a function of fixed capital stock K, variable inputs X, and fixed inputs Z:

$$Y = Y(K, X, Z). \tag{1}$$

For simplicity, we assume in what follows that output is produced using capital and other variable and fixed inputs. Let an entrepreneur also face fixed transaction costs given by T, which is a function of the concentration of firms producing similar and related goods in nearby areas. Such transaction costs can be incurred while procuring inputs and selling outputs. With the concentration of input suppliers and output buyers in close proximity, as in the case of industrial clusters, the transaction costs for an entrepreneur will be lower (Becattini 1990; Grabher 1993; Schmitz 1995). This could be due either to a reduced transportation cost stemming from proximity or to the developed networks among different agents that help to facilitate the transaction through the flow of information and mutual trust.

For a given level of capital stock and fixed inputs and prices of outputs and variable inputs, the short-run profit function for an entrepreneur is then given by

$$\pi(K, Z, w_X, p, T) = \max_{Y,X}\ pY - w_X X - T, \tag{2}$$

where π is profit, p is output price, and w_X is the variable input price.

Given the capital endowment of an entrepreneur, one would invest in a project if and only if there is a positive profit—that is,

$$\pi(K, Z, w_X, p, T) = \max_{Y,X}\ pY - w_X X - T \geq 0 \qquad (3)$$

and

$$\pi^1(K, Z, w_X, p) = \max_{Y,X}\ pY - w_X X \geq T, \qquad (4)$$

where $\pi^1(K, Z, w_{X,} p)$ is optimal profit excluding the fixed transaction costs T.

From the preceding formulation, let K^m be the capital stock at which, given the values of w_X, p, and Z, profit is equal to the fixed transaction costs T. In other words, K^m is the minimum capital stock required to start a business.

$$\pi^m(K^m, Z, w_X, p) = T\ , \qquad (5)$$

where $\pi^m(K^m, Z, w_X, p)$ is profit that equals the fixed transaction costs T at the minimum capital stock K^m.

Following the standard theory of profit maximization, the first-order derivative of profit with respect to capital is positive and equal to the shadow price of capital. At the point where the capital stock is equal to K^m, the shadow price of capital is then given by

$$\frac{\partial \pi^m(K^m, Z, w_X, p)}{\partial K} = w_K(K^m, Z, w_X, p) \geq 0, \qquad (6)$$

where w_K is the shadow price of capital.

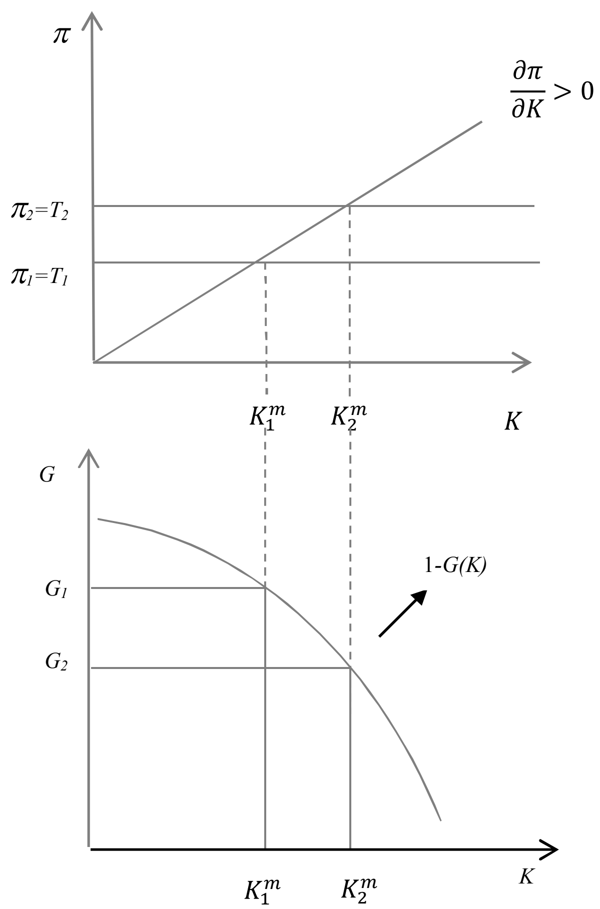
Because the first-order derivative is positive, it can be inferred from equations (5) and (6) that there is a positive relationship between the fixed transaction costs T and the minimum required capital stock K^m. This implies that a reduction in transaction costs (for example, due to clustering) will result in a reduction of the minimum initial capital amount required to start a business. This could be because an enterprise operating inside a cluster can specialize in activities for which it has a comparative advantage or because the other parts and components can be accessed easily at a lower cost from nearby firms. With an increase in transaction costs, on the other hand, the initial capital stock required is higher since the enterprise would have to produce the intermediate parts itself because it is costly to get them from the market. Krugman and Venables (1996) noted that with increased distance between firms, transaction costs tend to increase leading to the emergence of large and vertically integrated industries since the various firms that would provide parts and components are not found in nearby locations. With the concentration of producers of final and intermediate goods in close proximity, more division of labor and specialization would prevail requiring a relatively lower amount of capital to start a business (Lall et al., 2003).

Previously, we assumed there was a fixed capital endowment. In the case of a perfect capital market, entrepreneurs can adjust their capital stock to the profit-maximizing optimum, in which case the shadow price of capital equals the market price. However, if a business activity requires a higher level of start-up capital than the capital endowment, and that extra capital cannot be obtained from the capital market, then entrepreneurs become financially constrained. The high level of start-up capital would then prevent a large number of poorly endowed entrepreneurs from entry with only a few wealthy people being able to invest in a more integrated production. On the other hand, with the co-location of intermediate input suppliers and output buyers, there would be increased specialization and division of labor that lowers the required start-up capital. Hence, even in the absence of a well-functioning capital market, entrepreneurs in industrial clusters would be less likely to be financially constrained with a relatively large share of them investing according to their level of capital endowment. This argument is further depicted in Figure 3.1, which shows the relationship between start-up capital, transaction costs, and the proportion of entrepreneurs who can potentially invest, given their endowment.

Let the distribution of capital endowment be given by the function $G: [0, \overline{K}] \rightarrow [0,1]$, such that $G(K)$ is the proportion of entrepreneurs whose endowment is less than or equal to a certain capital amount K. That is, the proportion of entrepreneurs with an endowment less than or equal to zero is zero, and the proportion of entrepreneurs with an endowment less than or equal to $\overline{K}$, which is the highest capital amount required to start a business, is 1.

According to Figure 3.1, at relatively high transaction costs, T_2, the initial capital required to start a business is K_2^m and the proportion of entrepreneurs with a capital endowment greater than or equal to K_2^m is the distance from zero up to G_2. At lower transaction costs, T_1, a lower amount of initial capital, K_1^m , is required, which also corresponds to a larger proportion of potential entrepreneurs with capital endowment greater than or equal to K_1^m, given by the distance from zero up to G_1.

Figure 3.1 Transaction costs, entry barrier, and entrepreneurship



3.4 Data

3.4.1 Data Sources

For this study, we had full information on 4,347 microenterprises operating in the handloom sector in 118 districts of four different regions of Ethiopia, namely, Amhara, Tigray, Addis Ababa, and the Southern Nations, Nationalities, and People (SNNP). The data are obtained from the 2002–2003 Cottage/Handicraft Manufacturing Survey conducted by the Central Statistical Agency of Ethiopia (CSAE). In that survey, information specific to an enterprise, such as the value of its starting capital, whether it was financially constrained when it started its business, and its main sources of starting capital, is included. Information regarding the schooling, experience, and age of the owner-operator is also included. Out of the 4,347 establishments, the analysis and empirical estimation are made on 1,325 enterprises that are established in the five years prior to the time of the survey. Additional location-specific variables, such as distance to the nearest all-weather road, are obtained from the 2002–2003 Welfare Monitoring Survey conducted by the CSAE. We also use the CSAE's 2002–2003 Large and Medium Scale Manufacturing Survey to define clustering.

3.4.2 Definition of Key Variables

Clustering

Different indexes have been developed in the literature to measure the level of clustering of certain activities in certain locations. A *location quotient* that quantifies how concentrated a certain sector is in a certain location compared with a larger geographic unit is one of the widely used measures of clustering (O'Donoghue and Gleave 2004). The location quotient for the handloom sector is calculated for the most detailed spatial unit possible, the district, by using the zone, which is the higher spatial unit next to a district, as a reference point:

$$LQ_d = (H_d/M_d)/(H_Z/M_Z), \tag{7}$$

where LQ_d is the location quotient of the handloom sector at district d; H_d is employment of the handloom sector at district d; M_d is total manufacturing employment at district d; H_Z is employment of the handloom sector at zone z; and M_Z is total manufacturing employment at zone z. Here total manufacturing employment includes employment in micro-, medium-, and large-scale manufacturing industries. One possible limitations of this measure is that districts that have large share of handloom employment in the total manufacturing employment may have the same level of concentration index as those districts in which there is only one large enterprise operating in the handloom sector. Taking this into account, we checked if there are districts where only one enterprise is operating in the handloom sector and we did not find any in our data.

To calculate the location quotient, the Cottage/Handicraft Manufacturing Survey and the Large and Medium Scale Manufacturing Survey are used. The Cottage/Handicraft Manufacturing Survey is a large representative survey on micro enterprises covering more than 53,000 establishments both in urban and rural parts in 11 regions of the country. The sampling frame for this survey was obtained from the listing of the 2001–02 Population and Housing Census, which was conducted by CSAE. Taking into account population size and expected distribution of cottage industries, a two-stage stratified cluster sample design was used for regional (urban) capitals, major (other) urban cities, and rural areas (CSAE, 2003). For another eight urban centers a three-stage stratified cluster sample design was used to select the sample. In each case, sample units were selected systematically using probability proportional to size; size being adjusted to the number of cottage industries obtained from the 2001–02 Population and Housing Census (CSAE, 2003). The Large and Medium Scale Manufacturing Survey is a census data covering all large and medium size manufacturing establishments in the country.

Capital market inefficiency

Although one can reasonably assume that Ethiopia's capital market is not well developed, there could be differences between locations with respect to how accessible capital is from both formal and informal sources. Such differences could arise, for example, from the presence of banks and microfinance institutions and variations in household savings. To account for differences in level of access to both formal and informal finances, we define the level of capital market inefficiency in each district.

Under a perfect capital market, agents can borrow and lend freely at the market interest rate, and the marginal product of capital should be equal among enterprises and across different locations. Following the works of Zhang and Tan (2007), Hsieh and Klenow (2009), and Long and Zhang (2011), we use the variation in the marginal product of capital as a measure of capital market inefficiency, which is calculated as follows.

For a production function with a constant return to scale, the marginal product of capital MP_K is proportional to the average product of capital. If we assume a Cobb-Douglas production function of the form $Y = K^{\alpha}X^{\beta}Z^{\gamma}$, the marginal product of capital is given by

$$MP_K = \alpha\left(\frac{Y}{K}\right), \tag{8}$$

where Y is the value of output; K is the capital stock; X is the variable input; Z is the fixed input; and α, β, γ are the elasticities of output with respect to capital, variable inputs, and other fixed inputs, respectively. The financial market inefficiency is then calculated by taking the standard deviation σ of the logarithm of equation (8) at the district level d:

$$\text{Cap.Mkt.Inff}_d = \sigma\left(log\left(\alpha\frac{Y}{K}\right)\right)_d = \sigma\left(log\left(\frac{Y}{K}\right)\right)_d \tag{9}$$

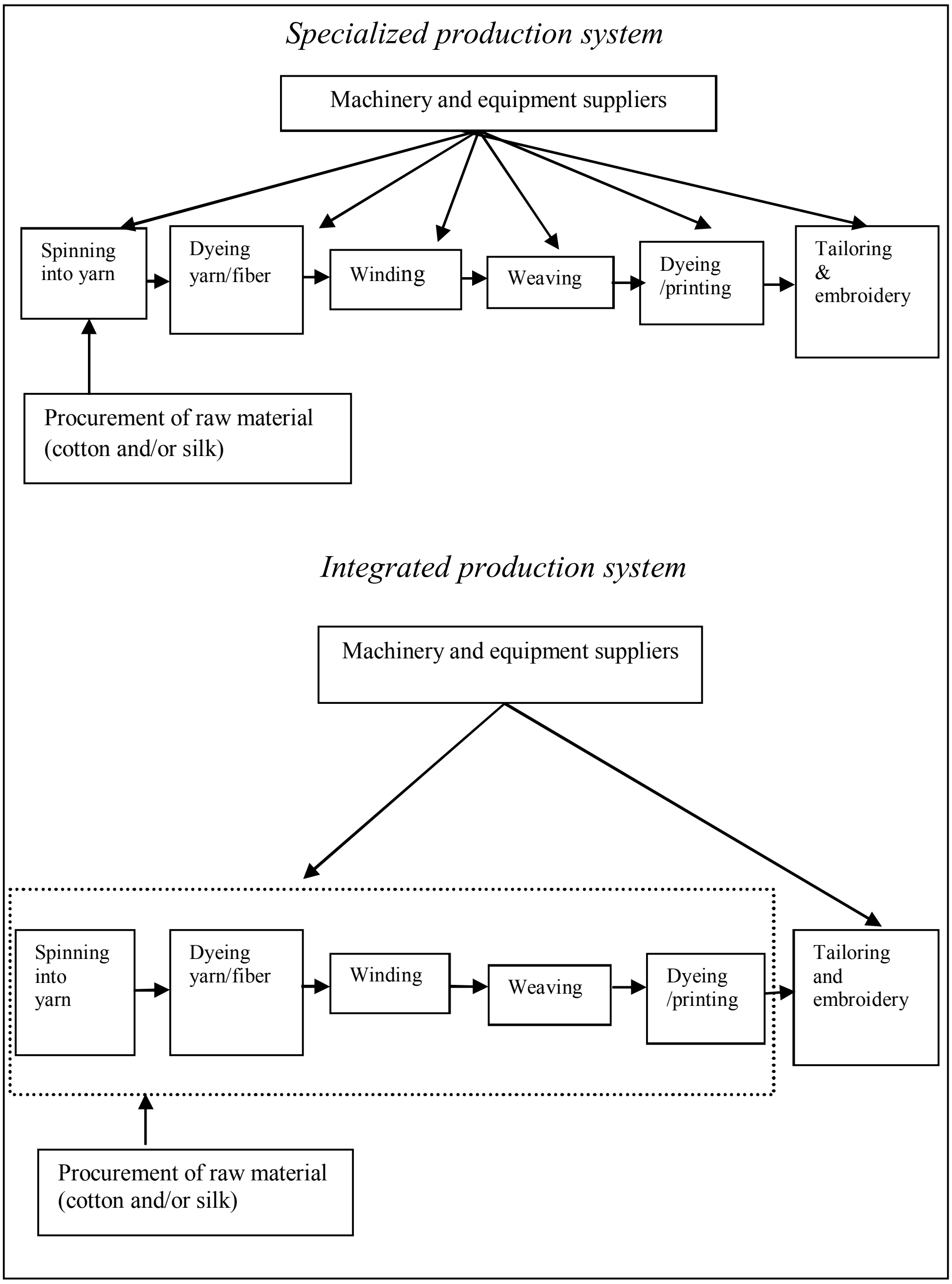
The preceding formulation indicates that in a perfect capital market, the standard deviation of the marginal product of capital among enterprises in a given district would be zero. The larger the deviation, the larger would be the financial market inefficiency. Data for the value of output and capital stock are obtained from the 2002–2003 Cottage/Handicraft Manufacturing Survey and the Large and Medium Scale Manufacturing Survey, both conducted by the CSAE. These data encompass enterprises in all the industries of different sizes.

3.5 Description of the Handloom Sector

The handloom sector engages more than 221,000 workers, 55 percent of whom operate in rural areas and 48.5 percent of whom are women (CSAE 2003). Producers in the sector often use simple tools, mainly specializing in hand-woven textiles and not using power-driven machines. Microenterprises in the handloom sector mostly consist of owner-operators with an average employment size of 1.4 persons. The sector comprises, on average, six different activities ranging from the spinning of cotton into yarn to the tailoring and embroidery of weaved products (Figure 3.2). These activities are either performed by different specialized producers or integrated in one enterprise. In the specialized system of production, often women engage in the pre- and post-weaving activities, whereas the weaving is predominantly done by males.

As with many other microenterprises in developing countries, financial constraint, especially when starting a business, is a major obstacle in the handloom sector. Table 3.1 shows this to be the case for 49 percent of the microenterprises in the survey. Microenterprises in the handloom sector also have limited access to loans from formal banks and lending agencies.

Figure 3.2 Specialized versus integrated production system in the handloom sector



As Table 3.1 depicts, none of the responding producers in the sample had borrowed money from a formal bank when starting his or her business. Instead, personal savings and informal sources of finance played an important role, with 43 percent and 23 percent of respondents having sourced their starting capital from own savings and friends and relatives, respectively. Assistance from government and nongovernmental organizations also represented a considerable share, while credit from microfinance institutions remained minimal at best (Table 3.1). The comparison between enterprises operating in more and less concentrated districts further indicates that a lower proportion, 42 percent, of producers operating in more concentrated districts were financially constrained when starting a business compared with 58 percent of producers in less concentrated districts.[8] Borrowing from friends and relatives was the most important source of start-up capital for enterprises in more concentrated districts, probably due to the importance of informal financing in industrial clusters. Own savings and informal money lenders, on the other hand, are important sources of start-up capital to enterprises operating in less concentrated districts (Table 3.1).

Microenterprises in the surveys reported average start-up capital of 132.69 birr (US$14.91)[9] (Table 3.2)[10]. That is even lower than the average minimum wage in the public sector, which is around 320 birr ($22.86) in 2010[11]. Using a more recent data of 2008 on handloom clusters in Ethiopia, Zhang et al., (2011) reported a similarly low average value of start-up capital that ranges from $12.82 in non-electrified rural areas to $21.68 in the capital city Addis Ababa.

Overall, initial investment levels are fairly low for microenterprises in the handloom sector compared with those of the large textile factories, which have an average initial investment level of 44,500,000 birr ($5,000,000) (Table 3.2). Microenterprises in more concentrated

[8] The distinction between more and less concentrated districts is made based on the median value of the location quotient at the district level.
[9] All dollars are U.S. dollars.
[10] The values in Table 3.2 are converted to U.S. dollars using the 5 years average exchange rate (1U.S.$ = 8.9 birr) from 1998–1999 until 2002–2003.
[11] The average exchange rate for 2010 was 1U.S.$ = 13.99 birr.

districts reported even a smaller amount of start-up capital compared with those in less concentrated districts (Table 3.2). Figure 3.3a shows a similar negative correlation between the value of start-up capital and the level of clustering as captured by the location quotient. Although informal finances, such as those from friends and relatives could enable entrepreneurs in industrial clusters to access finance and invest more, increased specialization and division of labor in industrial clusters, on the other hand, might reduce the start-up investment needed to establish a business.

Table 3.1 Problems upon starting a business and most important sources of capital

	Total		More concentrated districts		Less concentrated districts	
	Freq.	%	Freq.	%	Freq.	%
The most important problems faced when starting the business						
Financial constraint	2,121	48.74	890	41.96	1,231	58.04
Lack of technical know-how	354	8.14	164	46.33	190	53.67
Lack of working premises	99	2.28	49	49.49	50	50.50
Lack of access to raw material	74	1.70	44	59.46	30	40.54
Government rules and regulations	5	0.11	1	20.00	4	80.00
No problem	1,623	37.30	586	36.11	1,037	63.89
Others	75	1.72	20	26.67	55	73.33
Total	4,351	100.0	1,754	40.35	2,597	59.74
The most important sources of initial capital						
Informal sources						
Own savings	1,876	43.16	695	37.05	1,181	62.95
Friends and relatives	1,007	23.17	522	51.84	485	48.16
Informal money lenders	108	2.48	31	28.70	77	71.29
Inherited	139	3.20	53	38.13	86	61.87
Formal sources						
Large formal banks	0	0	0	0	0	0
Microfinance institutions	9	0.21	4	44.44	5	55.55
Assistance from government/non-gov. org.	923	21.23	363	39.33	560	60.67
Others	285	6.56	85	29.82	200	70.18

Source: The 2002–2003 Cottage/Handicrafts Manufacturing Survey.

Microenterprises operating in districts characterized by high levels of financial market inefficiency reported less start-up capital on average than those operating in districts with lower levels of financial market inefficiency (Table 3.2). Figure 3.3b also depicts a similar relationship—that is, a negative correlation between the value of start-up capital and the level of financial market inefficiency. This may illustrate the poor access to both formal and informal finances in financially inefficient districts, causing entrepreneurs to invest in activities that require relatively less capital.

Table 3.2 Comparison of average starting capital across regions and production systems (currency in birr)

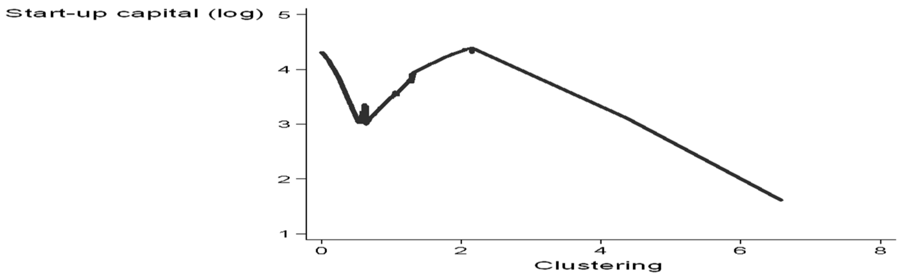
	Average starting Capital	Average capital-labor ratio
Large textile factories	44,500,000 ($5,000,000)	177,775.20
Microenterprises	132.69 ($14.91)	338.85
Tigray	157.37 ($17.68)	462.87
Amhara	123.84 ($13.91)	282.52
SNNP	96.52 ($10.84)	242.45
Addis Ababa	175.56 ($19.73)	491.27
More concentrated districts	123.53 ($13.87)	263.19
Less concentrated districts	149.89 ($16.84)	480.77
Districts with high financial inefficiency	114.36 ($12.85)	359.54
Districts with low financial inefficiency	155.27 ($17.45)	410.84

Source: The 2002–2003 Cottage/Handicrafts Manufacturing Survey and the 2002–2003 Large and Medium Scale Manufacturing Survey. Notes: The average start-up capital is calculated only for the newly established enterprises, that is, those formed in the five years preceding the survey. The average exchange rate from 1998–1999 until the time of the survey, 2002–2003, was 1 US$ = 8.9birr. SNNP = Southern Nations, Nationalities, and People.

Tables 3.1 and 3.2 show two important points that correspond with the predictions of the theoretical model presented in Section 3.3. First, the majority of microenterprises in highly concentrated districts were not financially constrained when starting their business. In addition, they reported low start-up capital versus those operating in less concentrated districts. This could be a result of specialization and division of labor in more concentrated districts that lowers capital entry barriers for entrepreneurs, enabling them to invest in activities that best suit their capital endowment without them necessarily being financially constrained. In addition, the informal financing that is common in industrial clusters could also have played a role in easing their financial constraint when establishing a business.

Figure 3.3 Correlation between clustering, start-up capital, and capital market inefficiency using locally weighed least-squared smoothing technique.

a. Start-up capital versus clustering



b. Start-up capital versus capital market inefficiency

Source: Constructed based on the 2002–2003 Cottage/Handicrafts Manufacturing Survey and the 2002–2003 Large and Medium Scale Manufacturing Survey. Note: The correlation is depicted for newly established enterprises, that is, those formed in the five years preceding the time of the survey. The unit of the start-up capital is birr.

Second, the majority of those in less concentrated districts were financially constrained and yet had higher start-up capital costs compared with those operating in more concentrated districts. This may be because those investing in less concentrated districts follow a more integrated form of production due to the absence of firms providing parts and components in nearby areas, which could then result in relatively higher start-up capital costs. In the absence of a well-functioning capital market, the high start-up capital costs might cause the majority of entrepreneurs investing in less concentrated areas to be financially constrained. The capital-to-labor ratios in Table 3.2 also show that producers in less concentrated districts were relatively more capital intensive than their more concentrated counterparts.

3.6 Empirical Model

To investigate the relationship between clustering and starting capital, we formulate the following OLS regression where the dependent variable is value of initial capital investment by each enterprise i (K_i).

$$K_i = \beta_1 LQ_d + \beta_2 \text{Cap. Mkt. Inff}_d + \beta_3 R_d + \beta_4 W_i + \gamma E + \varepsilon. \qquad (10)$$

We would expect β_1 to be negative; that is, with increased clustering, entrepreneurs tend to invest a lower amount of capital due to a reduced entry barrier following specialization and division of labor in industrial clusters. Similarly, β_2 is expected to be negative indicating that with increased financial market inefficiency, entrepreneurs tend to have a limited access to capital (both formal and informal) that could then lead them to invest in activities that require a relatively lower start-up investment.

The average distance at each district level from the nearest all-weather road is depicted by R_d. This variable is used as an indicator of the value of the location in which the entrepreneur is establishing a business. For example, accessible locations with good infrastructure might be valued higher than remote locations. This can be reflected by a high value of land or high rental prices for buildings, which could also increase the start-up capital. The wealth of an entrepreneur, indicated by W_i, can also affect how much can be invested in the business. For example, it might be easier for wealthy entrepreneurs to either invest their own savings or have enough collateral that could reduce their cost of borrowing. As an indicator of wealth, we use a dummy that captures whether an entrepreneur owns a non-residential building or not.

E is a vector of enterprise-specific factors such as the age, schooling, and gender of the owner-operator. Regional and urban dummies are also included to capture regional variations. The corresponding enterprise-specific parameters are captured by the vector γ, and ε is a random term. Due to unavailability of data, we are unable to control for the possibility of differences in relative input prices across locations, which could have an effect on the initial investment size.

We further investigate the relationship between starting capital and clustering between enterprises investing in districts of low and high capital market inefficiencies. The distinction is made based on the median value of the capital market inefficiency at the district level. Based on this, two separate regressions are performed for the two groups where the coefficients of the location quotient are compared. We would expect the impact of clustering in reducing the entry barrier of the initial capital investment to be higher (in absolute terms) for microenterprises investing in districts with high capital market inefficiencies.

3.7 Empirical Results

Location-specific variables such as clustering as captured by the location quotient, level of capital market inefficiency, and distance to the nearest all-weather road; and enterprise-specific variables such as the age and schooling of the owner-operator are all based on current information at the time of the survey. On the other hand, information on start-up capital was asked for at the time of the survey but involves information about the time when the business was actually established. Due to the gap in timing between the dependent and many of the explanatory variables, we have restricted the regression analyses to only enterprises established in the five years previous to the time of the survey. Twenty-five percent of enterprises in the sample started their business during this period, giving us 1,325 observations with which to do the regressions.

3.7.1 Clustering and Starting Capital

Taking the logarithm of start-up capital as the dependent variable, column II of Table 3.3 shows that clustering, as captured by the location quotient, reduces start-up capital. Similarly, the greater the capital market inefficiency of a certain district, the lower the start-up capital is, implying the existence of limited access to both formal and informal finances in such locations. Entrepreneurs in accessible locations, as captured by distance to the nearest all-weather road, invest a relatively larger amount of capital than do those in remote areas. On the other hand, entrepreneurs in urban areas invest relatively less capital than do those in rural areas. Whereas the first result may capture the higher valuation of accessible locations that could increase the initial investment size, the urban dummy variable, on the other hand, may have wider implications in terms of capturing the externalities from the existence of large firms and other complementary services in urban areas that may reduce the transaction costs of operating a business (Krugman 1991; Fujita et al., 1999). Large urban areas are also more diverse, supporting a wide range of industrial activities in close proximity (Fujita et al., 1999), which may help facilitate specialization and the division of labor. Interestingly, the coefficient of the urban dummy variable is much higher than that of clustering, which may indicate that the externalities and multiple specializations in urban centers have a greater impact on helping to reduce starting capital.

Entrepreneurs who own non-residential buildings invest a relatively larger amount of capital than do those who do not own such buildings. This shows that more wealth leads to higher savings, which one can either invest in a business or use to gain relatively better access to capital due to availability of collateral.

Male entrepreneurs are found to invest relatively larger amounts of capital than their female counterparts. The relatively limited savings (McKee 1989; Otero and Downing 1989) and lack of access to both formal and informal sources of finance among women entrepreneurs (FAO 1984) may lead them to invest in activities that have a lower entry barrier. Similarly, more educated and young entrepreneurs are found to make larger investments compared with less educated and older entrepreneurs. This could be due to better information-processing ability and search techniques regarding markets in general and credits in particular among more educated and young entrepreneurs (Wheeler 2006; Freedman 2008), which may result in them taking calculated risks to invest in activities that require larger investments with higher returns.

Columns III and IV of Table 3.3 show the comparison of the impact of clustering on start-up capital between enterprises investing in districts with low and high capital market inefficiency, respectively[12]. As expected, the impact of clustering on reducing start-up capital is higher for enterprises investing in districts with high capital market inefficiency, which illustrates the importance of industrial clusters as an alternative to propagate industrialization when the local conditions do not allow easy access to credit.

[12] A Chow test between the whole sample of enterprises and those investing in districts with high capital inefficiency shows a significant difference in coefficients across the two, justifying the need to have separate regressions for enterprises in low and high financially inefficient districts.

Table 3.3 Clustering and starting capital

	Starting capital (log)		
	Full Sample	Low capital market inefficiency	High capital market inefficiency
Clustering (location quotient)	-0.13**	-0.17**	-0.28***
	(0.05)	(0.09)	(0.06)
Capital market inefficiency (log)	-0.19***	—	—
	(0.06)		
Distance to all-weather road (log)	-0.07**	-0.27***	0.07*
	(0.03)	(0.05)	(0.04)
Own building (dummy)	0.43***	0.76***	0.08
	(0.09)	(0.11)	(0.14)
Male (dummy)	2.20***	2.07***	2.14***
	(0.08)	(0.12)	(0.13)
Years of schooling	0.04***	0.02	0.04***
	(0.01)	(0.02)	(0.02)
Age	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)
Addis Ababa (dummy)	0.72***	0.28	1.13***
	(0.12)	(0.21)	(0.17)
Amhara (dummy)	0.14	0.15	-0.04
	(0.11)	(0.14)	(0.16)
Tigray (dummy)	0.63***	0.42***	0.71***
	(0.12)	(0.14)	(0.24)
Urban (dummy)	-0.35***	-0.39	-0.53
	(0.13)	(0.18)**	(0.21)**
R^2	0.478	0.470	0.510
N	1,325	636	689

Notes: Robust standard errors are reported in parentheses.
Significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

3.7.2 Robustness Check Using a Different Measure of Clustering

In this section, we check the robustness of the preceding results by using a different measure for clustering. Following the works of Adelman (1955), Levy (1991), Holmes (1999), and Sonobe and Otsuka (2006b), we use the average sales-to-value-added ratio of enterprises at the district level as a measure of clustering. This ratio tends to increase as the number of enterprises involved in the production process increases. The ratio therefore captures the concentration of specialized firms in a given district.

Table 3.4 Clustering and starting capital (using alternative measure of clustering)

	Starting capital (log)		
	Full Sample	Low capital market inefficiency	High capital market inefficiency
Clustering (sales-to-value-added ratio)	-0.04**	-0.05**	-0.11***
	(0.02)	(0.03)	(0.04)
Capital market inefficiency (log)	-0.21***	—	—
	(0.06)		
Distance to all-weather road (log)	-0.07**	-0.27***	0.09**
	(0.03)	(0.05)	(0.04)
Own building (dummy)	0.43***	0.69***	0.15
	(0.09)	(0.11)	(0.14)
Male (dummy)	2.19***	2.06***	2.14***
	(0.08)	(0.12)	(0.13)
Years of schooling	0.04***	0.02	0.04***
	(0.01)	(0.02)	(0.02)
Age	0.00	0.01	-0.00
	(0.00)	(0.00)	(0.00)
Addis Ababa (dummy)	0.67***	0.27	1.20***
	(0.12)	(0.22)	(0.18)
Amhara (dummy)	0.14	0 .11	0.17
	(0.11)	(0.14)	(0.18)
Tigray (dummy)	0.55***	0.27*	0.64**
	(0.12)	(0.14)	(0.25)
Urban (dummy)	-0.33**	-0.39**	-0.47**
	(0.13)	(0.18)	(0.20)
R^2	0.478	0.469	0.511
N	1,325	636	689

Notes: Robust standard errors are reported in parentheses.
Significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

The sales-to-value-added ratio, however, might be affected over time through a change in the prices of outputs and inputs, and it may not really capture the concentration of specialized firms (Sonobe and Otsuka 2006b). Having that shortcoming in mind, we checked the correlation between the location quotient and the sales-to-value-added ratio for the newly established enterprises at the district level, and we find that the two measures of clustering are positively correlated.

As can be seen in column II of Table 3.4, similar significant effects are found where an increase in the average sales-to-value-added ratio at the district level reduces the amount of start-up capital, even after controlling for financial market inefficiency. The comparison between microenterprises investing in districts with low and high capital market inefficiency also show the effect to be significantly larger for those investing in districts marked by high capital market inefficiency (column III and IV, Table 3.4).

3.7.3 Mechanism Check: Clustering and Likelihood of Being Financially Constrained

In the preceding section, we found that starting capital is lower for those investing inside clusters. In this section, we check if this is actually due to a low capital entry barrier inside clusters. For this, we formulate another regression to investigate the relationship between clustering and the likelihood of being financially constrained when starting a business. If the reduction in starting capital within clusters is due to a low capital entry barrier, we would then expect being financially constrained not to be a major concern for those investing inside clusters. In other words, if clustering is associated with low capital entry barrier, microenterprises investing inside clusters are expected to have a lower likelihood of being financially constrained when starting a business. We try to capture this by the following probit regression using the same explanatory variables as in the previous OLS regression.

$$P(FC)_i = \beta_1 Clustering_d + \beta_2 \text{Cap.Mkt.Inff}_d + \beta_3 R_d + \beta_4 W_i + \gamma E + \varepsilon \qquad (11)$$

In the 2002–2003 Cottage/Handicrafts Manufacturing Survey, producers were asked to state the most important problem they faced when starting their business. They were provided with different types of business related constraints to rank, where one of them was being financially constrained. Based on these responses, we define a dummy (FC) that has a value of one if a producer responded that being financially constrained was the most important problem he or she faced when starting a business and zero otherwise. $P(.)$ is the probability that FC =1.

Table 3.5 reports the marginal effects of the probit regression. As expected, clustering reduces the likelihood of being financially constrained when starting a business and the result is robust for the different measures of clustering. This illustrates that the reduction in starting capital inside clusters is indeed due to a low capital entry barrier, which allows entrepreneurs to invest their limited endowments without necessarily being financially constrained.

An increase in the level of capital market inefficiency in a given district, increases the likelihood of an entrepreneur being financially constrained when starting a business. Similarly, investing in accessible locations increases the probability of being financially constrained, which is probably due to the increased value of the location that requires a greater amount of start-up capital. Male entrepreneurs in general are less likely to be financially constrained when starting a business than female entrepreneurs. Studies have shown that female entrepreneurs in developing countries generally lack economic resources that can be used as collateral to access credit (FAO 1984; McKee 1989; Otero and Downing 1989; Buvinic and Marguerite 1990). Culture, social norms, and the type of activities women invest in have also been mentioned as possible factors contributing to their limited access to both formal and informal finances (McKee 1989).

Entrepreneurs with more years of schooling are less likely to be financially constrained when starting a business. This could be because more educated entrepreneurs are more informed about different ways of gaining access to credit than their less educated counterparts. In addition, educated entrepreneurs might appear creditworthy in the eyes of lenders because of their relative credibility in taking calculated risks and their bookkeeping ability that could help facilitate the monitoring process.

Table 3.5 Clustering and likelihood of being financially constrained

Marginal effects of probability of being financially constrained		
Clustering (location quotient)	-0.28***	
	(0.03)	—
Clustering (sales-to-value-added ratio)	—	-0.02***
		(0.01)
Capital market inefficiency (log)	0.09***	0.04**
	(0.02)	(0.02)
Distance to all-weather road (log)	-0.03***	-0.02**
	(0.01)	(0.01)
Own building (dummy)	-0.03	-0.02
	(0.03)	(0.03)
Male (dummy)	-0.19***	-0.21***
	(0.03)	(0.03)
Years of schooling	-0.01**	-0.01**
	(0.01)	(0.01)
Age	-0.00	-0.00
	(0.00)	(0.00)
Addis Ababa (dummy)	-0.11**	-0.23***
	(0.06)	(0.05)
Amhara (dummy)	0.05	0.07
	(0.04)	(0.04)
Tigray (dummy)	-0.03	-0.15***
	(0.05)	(0.05)
Urban (dummy)	-0.04	-0.01
	(0.05)	(0.05)
N	1,325	1,325

Notes: Robust standard errors are reported in parentheses.
Significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

3.7.4 The Issue of Causality

Although the preceding results show the relationship between clustering and capital entry barriers, the issue of causality could be a concern if there are any unobservable factors correlated with clustering that can have an effect on start-up capital. The fact that we have a cross-section data set, and not a panel data set so the time dimension of variables is not included, may result in omitted variable bias due to unobservable factors across enterprises. Due to lack of valid instruments to control for biases that may arise from unobservable factors, we perform a “placebo” test by taking large firms that have better access to credit as a control group and analyse the relationship between clustering and start-up capital in their respective situations. Such approach allow us to reduce the risk of endogeniety, if not eliminate it entirely, by showing that clustering reduces start-up capital only when there is a lack of access to external financing and not because unobservable factors not captured by the model are at work.

Compared to micro- and small-scale enterprises, the large firms in Ethiopia, particularly state-owned and foreign-owned firms, have better access to credit (World Bank 2009b). According to the investment climate survey conducted by the World Bank in 2001–2002 and 2006–2007, large firms and especially state-owned ones are far less likely to identify themselves as constrained by costs of financing because they tend to have collateral either through ownership of buildings or land. In addition, the concentration of the banking sector by state-owned banks (nearly two-thirds of the banking system) has resulted in preferential treatment for state-owned and large firms (World Bank 2009b). Large firms with better access to credit are therefore more likely to use the integrated mode of production and hence clustering would be less important for them at least in terms of reducing starting capital.

Table 3.6 shows the regression results of the logarithm of starting capital on the two measures of clustering[13], capital market inefficiency, and other explanatory variables using the 2002–2003 census data of the CSAE’s Large and Medium Scale Manufacturing Survey. The regression, which is performed on the firms established in the five years preceding the time of the survey, shows that the clustering variables in both columns have the expected signs but are not significant, implying that clustering is not important when there is better access to credit. Although the regression is not done based only on data from the textile

[13] Clustering of large firms is calculated at the zonal level by taking regions as a reference point.

industry[14], the results in Table 3.6 show that clustering relates differently for producers with different levels of access to credit. However, these results should be interpreted with caution because even if the effect is zero, there may also be other differences between small and large firms that are responsible for this result.

Table 3.6 Placebo test on the role of clustering on starting capital for large firms with good access to credit

	Starting Capital (log)	
Clustering (location quotient)	-0.11	—
	(0.38)	
Clustering (sales-to-value-added ratio)	—	-0.11
		(0.45)
Capital market inefficiency (log)	-0.32	-0.51
	(1.14)	(0.86)
Distance to all-weather road (log)	0.36	0.45
	(0.36)	(0.31)
Own building (dummy)	2.16***	2.16***
	(0.39)	(0.39)
Male (dummy)	1.16*	1.14*
	(0.59)	(0.59)
Public (dummy)	3.47***	3.47***
	(0.58)	(0.58)
Foreign (dummy)	1.62***	1.63***
	(0.56)	(0.56)
Addis Ababa (dummy)	0.32	0.51
	(0.84)	(0.97)
Amhara (dummy)	0.28	0.25
	(1.01)	(0.89)
Tigray (dummy)	-0.06	-0.16
	(0.97)	(1.13)
Urban (dummy)	1.18	1.07
	(0.74)	(0.82)
R^2	0.206	0.206
N	153	153

Notes: Demographic information other than gender is not available about the owner of the firm. Sectoral dummies for different manufacturing activities are included in the regression but not reported in the table. Robust standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

[14] Because the number of newly established manufacturing firms in the textile sector is very small (only seven firms), the regression is done for all manufacturing firms and by including sectoral dummies.

3.8 Conclusions and Discussion

Microenterprises in developing countries often struggle with financial constraints. The absence of a well-developed capital market has been listed as a key obstacle to industrialization in developing countries in the development literature (Bigsten et al. 2003; Hernández-Trillo et al., 2005; McKenzie and Woodruff 2006, 2008). In this paper, we show that industrial clusters, through specialization and division of labor, can ease the financial constraints of microenterprises even in the absence of a well-functioning capital market. By using data from microenterprises of the handloom sector in four regions of Ethiopia, we find that clustering lowers capital entry barrier by reducing the initial investment required to start a business. This effect is found to be significantly larger for enterprises investing in districts of high capital market inefficiency. The results are also robust for different measures of clustering.

Even if financial development is crucial for industrial development, developing a well-functioning capital market is a daunting task. Clustering could therefore be an alternative way to propagate industrialization when local conditions do not allow easy access to credit. China has achieved rapid industrialization in the past three decades despite its lack of a well-functioning capital market. Clustering largely explains how Chinese micro- and small-scale enterprises were able to function in a credit-constrained environment (Huang et al. 2008; Ruan and Zhang 2009; Long and Zhang 2011). Even if the institutional contexts in which clusters operate are not the same as in China, the cluster-based industrialization model may be applied to developing countries in Africa with similar capital endowments. Promotion of clusters, especially in divisible sectors, could therefore help developing countries engage the vast number of entrepreneurs in micro- and small-scale industries in production processes and make better use of limited capital.

A possible caveat of this study is its reliance on cross-sectional data, which does not allow us to see the effects of inter-temporal changes of relative prices. That we cannot entirely control for possible unobservable factors that can be correlated with clustering is another limitation. In addition, due to lack of detailed data on forward and backward linkages between different agents within clusters, we could not identify the potential mechanisms that could explain the cluster effects, such as the promotion of trust through repeated interaction, the exchange of information and promotion of cooperation, which all can facilitate access to finance. Despite these shortcomings, however, the results of this study show the role of clustering as one way of enhancing industrialization in developing countries by fostering entrepreneurship and by reducing capital entry barriers.

CHAPTER 4

Farm households and non-farm activities in Ethiopia: does clustering influence entry and exit?[♣]

Abstract: *This paper examines how clustering affects the entry and exit decisions of farm households into and from non-farm enterprises in rural Ethiopia. It is found that the existence of clusters of micro enterprises in the same district increases the likelihood of rural households to start a non-farm enterprise. Similarly, clustering of big manufacturing firms in the same zone is found to increase the likelihood of farm households to start a non-farm enterprise. Non-farm enterprises operating in clusters are also found to have a lower probability of exit than those operating outside of clusters. The study further investigates the impact of entry and exit into and from non-farm enterprises on farm household's well-being by using total household income, the food security status of a household and the household's ability to raise enough money in case of emergency, as indicators. Using propensity score matching to account for selection bias, it is found that, entry into non-farm enterprises significantly increases household's income and food security status. Exit from non-farm enterprises, on the other hand, is found to significantly reduce household's income.*

Keywords: non-farm enterprise, clustering, entry and exit, household's well-being, Ethiopia, Africa.

[♣] Paper by Merima Ali and Jack Peerlings, Forthcoming in *Agricultural Economics.*

4.1 Introduction

Poverty and income variability remains one of the biggest challenges facing most rural households in Sub-Saharan Africa (SSA). Even though agriculture is the main source of income for more than 85% of the rural population in the region, the dwindling size of agricultural land due to increasing population, low productivity and hostile agro ecological factors often result in extreme income variability. One of the mechanisms used by rural households to smooth income variability is to diversify their activities by starting non-farm enterprises (NFEs). Evidence suggests that close to 37% of income for rural households in Africa is derived from non-farm activities despite the fact that only 9-19% of the rural labor force is employed in such activities (Haggblade et al., 2007). NFEs are particularly important in generating income and employment for the poorest segment of the society, particularly women and unskilled labor (Nadvi and Barrientos, 2004). In addition to income-earning opportunities, the promotion and establishment of rural NFEs are also noted to play an important role in reducing food insecurity in rural Africa (Barrett et al., 2001).

Yet, rural households face various constraints when establishing and expanding NFEs such as lack of capital, limited market access and technical knowhow, poor information access, etc. Public goods like infrastructure, research and training centers and government and regulatory institutions are often absent in rural areas because of high cost due to lower population densities, having negative implications for economies of scale (Eifert and Ramachandran, 2004; Collier and Venables, 2008). This results in higher transaction costs both for establishing and expanding businesses in rural areas implying significant entry barriers and high exit rates in NFEs (Haggblade et al., 2007). The total closure rate among rural NFEs in Africa is quite high[15] where the likelihood of exiting is found to be common among newly established ones (Liedholm and Mead, 1999; Liedholm, 2007; Loening et al., 2008).

[15] For example, the total closure rate of NFEs in Ethiopia is 25% (Loening et al., 2008).

In recent literatures, industrial clusters are noted as one form of institution that can help to reduce the various transaction costs faced by enterprises both when establishing and during the operation of businesses (Sonobe and Otsuka, 2006a; Ruan and Zhang, 2009; Ali and Peerlings, 2011a). Clustering, through specialization and division of labor, can lower entry barriers by reducing the initial capital required to start a business, even in the absence of a well-functioning capital market (Huang et al., 2008; Ruan and Zhang, 2009; Ali et al., 2010). The barriers to start a business can also be lower in industrial clusters than in dispersed locations because specialized inputs, local market and customers are readily available (Porter, 2000). Established relationships and social networks with various agents in the same community and the presence of "successful" local firms can also reduce the perceived risk of entry (Porter, 2000). Even after establishment, the presence of strong cluster environment that fosters growth and enhances regional comparative advantage plays an important role for the survival of enterprises (Schmitz,1995; Schmitz and Nadvi, 1999; Ali and Peerlings, 2011a).

In clusters there may also be forces that increase the entry cost and threaten the survival of the already established businesses by diminishing the returns to entrepreneurial activity (Delgado et al., 2010). This may occur from external diseconomies of scale such as air pollution, congestion, and fierce competition for limited markets and resources such as land and specialized inputs (Lall et al., 2003; Delgado et al., 2007; Sonobe and Otsuka, 2006a).

The purpose of this study is to investigate how clustering affects the entry and exit decisions of farm households into and from NFEs in rural parts of Ethiopia. Several studies have examined the determinants of household's decisions to diversify to NFEs in developing countries (for example; Abdulai and Delgado, 1999; Barrett et al., 2001; Owusu et al., 2011). Most of these studies focus on the impact of household, farm and village characteristics, and some exogenous factors like rainfall and price variability in affecting the decision of households to diversify to NFEs. However, empirical work on the possible impact of clustering on entry costs for establishing NFEs and hence households' diversification decision is quite scarce (Huang et al., 2008; Ruan and Zhang, 2009). In addition, data on firm dynamics, particularly on micro enterprises is rarely available in SSA making studies on the determinants of exit decisions non-existent except for larger firms (McPherson, 1995; Harding et al., 2004; Bigsten and Gebreeyesus, 2007; Gebreeyesus, 2008). To the best of our knowledge, this is the first empirical work that looks at the entry and exit decisions of farm households into and from rural NFEs in Africa from a clustering point of view.

The study further investigates the impact of entry and exit into and from NFEs on household's well-being by using total household income, the food security status of a household and the household's ability to raise enough money in case of emergency, as indicators. Participation into a NFE is hardly a random process where households with certain characteristics might self-select themselves both in the decision of entering into and exiting from NFEs. Failure to address the selection-bias may therefore result in wrong estimates of the impact of entry and exit into and from NFEs on household's well-being. In order to address this issue, we use the non-parametric statistical method of propensity score matching where the well-being of households that have entered and exited NFEs is compared with counterfactual groups of households that have not entered and have not exited NFEs respectively. The data for this study is from the 2006/07 Rural Investment Climate Survey (RICS) collected by the World Bank together with the Central Statistical Authority of Ethiopia.

The remainder of the paper is organized as follows. Section 4.2 presents the theoretical framework for the entry and exit decisions of households into and from NFEs. Section 4.3 discusses the data and section 4.4 presents the empirical model. Section 4.5 presents the empirical results and section 4.6 provides a conclusion and discussion.

4.2 Theoretical Framework: Entry and Exit Decisions of Households into and from Non-farm Enterprises.

A series of studies on rural non-farm activities underline the importance of profit maximization and risk minimization or income stabilization as the major motives for farm households' decision to diversify beyond agriculture (see, for example, Haggblade et al., 2007; Rose, 2001). The profit maximization motive is driven by "pull" factors that are characterized by available markets and opportunities, infrastructural facilities and supportive institutions, etc. Various idiosyncratic shocks such as drought, environmental degradation, chronic rainfall deficit etc., on the other hand, may "push" households to diversify beyond agriculture as a risk management strategy in order to smooth income over time. Although it is important to understand the broader set of households' motives to diversify beyond agriculture, we base our theoretical framework on the profit maximization motive, because it will best serve the main objective of the study, which is to investigate the effect of location specific "pull' factor of clustering on households' diversification decision[16].

Let a farm household faces two choices; either to continue working in agriculture or to diversify its activity by starting a NFE. Each household will make a choice based on a comparison of the expected post-entry NFE profit to forgone agricultural income due to diversification. That is, a household will start a NFE if its expected enterprise profit is higher than the forgone agricultural income from diversification. Otherwise, the household chooses to continue its agricultural work. Next we will formalize this idea.

Suppose a household has fixed endowments of labor and capital that it has to allocate among different activities. When household i is engaged only in agriculture, the present value of agricultural income is given as:

[16] Even if the motive of the household is profit maximization, exogenous shocks affecting agricultural income may still influence its expected profit, and hence the diversification decision.

$$PV_i = E_t \sum_{\tau=t}^{T} \beta^{\tau-t}\, \pi_i(p_A, w_{A,} Z_i, \varphi_t, \varepsilon_i), \qquad (1)$$

where E_t is the expectation operator given the information set at time t, β is the subjective discount factor, T is the number of periods and π_i is agricultural profit of household i. Agricultural profit is a function of prices of agricultural outputs (p_A) and inputs (w_A) and endowments of the fixed inputs; labor and capital (Z_i). φ_t is a vector of exogenous shocks that one way or the other can affect agricultural income like rainfall variability, drought, flooding, price shocks etc. ε_i is household and farm specific unobservable characteristics that affect agricultural income.

In the case of diversifying its activity by starting a NFE, the household will face entry barriers that can be affected by location specific factors like industrial clusters and the investment climate,[17] the level of investment capital required to start the business and skill requirements.

Upon diversification, the household will have the following present values of income from the agricultural (A) and NFE (B).

$$PV_{A,i} = E_t \sum_{\tau=t}^{T} \beta^{\tau-t}\, \pi_{A,i}(p_A, w_{A,} Z_{A,i}, \varphi_t, \varepsilon_i), \qquad (2)$$

$$PV_{B,i} = -C_{i,t}(N_l, I_l, H_i) + E_t \sum_{\tau=t}^{T} \beta^{\tau-t}\, \pi_{B,i}(p_B(N_l, I_l), w_B(N_l, I_l), Z_{B,i}, \mu_i), \qquad (3)$$

$$Z_i = Z_{A,i} + Z_{B,i} \qquad (4)$$

Since the household is a price taker, the prices of agricultural outputs (p_A) and inputs (w_A) do not change whether the household works only in agriculture (equation 1) or diversifies

[17] Investment climate is defined as different characteristics specific to a certain location that could act as incentives or disincentives for running a business like availability of financial services, infrastructure, governance, regulations, taxes, conflict resolution, etc (Eifert and Ramachandran, 2004).

with NFE (equation 2). The household has to allocate the total amount of fixed inputs of labor and capital across the different activities as formulated in (4).

In equation 3, $C_{i,t}$ denotes the cost of entry in to a NFE. The entry cost can be affected by location specific characteristics like the investment climate (I_l) that can be captured by factors like availability of financial services, infrastructure, government regulations and taxes, safety of the locations, etc., which could increase or lower the entry barrier. These characteristics can capture the policies, institutional arrangements and infrastructure of a certain location and the effect they may have on transaction costs of entering a business. The cost of establishing a NFE can also be affected by the existence of concentration of other enterprises (industrial clusters) in the same location(N_l). In addition to location specific variables, the minimum required skills or entrepreneurial ability to run a NFE can also be a barrier to enter a NFE. Although it is difficult to directly capture the inherent ability of individuals; the age, gender, and schooling of an entrepreneur, in this case a household head, can be used as an indicator and this is denoted by H_i.

Post entry NFE profit in equation 3 is a function of output and input prices of the NFE denoted by p_B and w_B respectively. Input and output prices can further be affected by location specific factors that can have an impact on the transaction costs of procuring inputs and selling outputs like reduced transportation cost stemming from proximity of input suppliers and output buyers as in the case of industrial clusters. Other location specific variables like existence of big firms and other complimentary services may also facilitate the transaction of inputs and outputs (Krugman, 1991; Fujita et al., 1999).

μ_i is enterprise specific and location specific unobservable characteristics that affect NFE income.

The household will choose to diversify by starting a NFE if and only if the present value of income from NFE is greater than the present value of forgone agricultural income from diversification (equation 6).

$$PV_{A,i} + PV_{B,i} > PV_i \tag{5}$$

$$PV_{B,i} > PV_i - PV_{A,i} \tag{6}$$

Following this, the probability $(prob)$ that household i chooses to diversify its activity by starting a NFE is given as:

$$prob_{(B,i)} = prob\left(-C_{i,t}(N_l, I_l, H_i) + E_t \sum_{\tau=t}^{T} \beta^{\tau-t}\, \pi_{B,i}\big(p_B(N_l, I_l), w_B(N_l, I_l), Z_{B,i}, \mu_i\big)\right) >$$
$$prob\left(E_t \sum_{\tau=t}^{T} \beta^{\tau-t} \left(\pi_i\big(p_A, w_{A,} Z_i, \varphi_t, \varepsilon_i\big) - \pi_{A,i}\big(p_A, w_{A,} Z_{A,i}, \varphi_t, \varepsilon_i\big)\right)\right) \tag{7}$$

In the right hand side of equation (7), the price of agricultural outputs (p_A) and inputs (w_A) do not change whether the household works only in agriculture or diversifies its activity. As a result we do not expect them to play a role in affecting household's choice of activities except that they determine the actual level of profit. What differs in the choice of the two activities is the amount of fixed inputs of labor and capital, hence it is expected that household's labor and capital endowments do play a role in the decision to start a NFE.

Let $d_{(B,i)} = 1$ if household i chooses to diversify its activity by starting a NFE and 0 if it chooses to continue agricultural production. If we assume that the stochastic components μ_i and ε_i are independently and identically distributed, then the probability of entry into a NFE is given by:

$$prob_{(B,i)} = \begin{cases} f(H_i, Z_i, N_l, I_l, \varphi_t) & if\ d_{(B,i)} = 1 \\ 0 & otherwise \end{cases} \tag{8}$$

After starting a NFE, an incumbent household once again faces two choices; either to continue its diversified activity or to exit the NFE and go back to agricultural production. In the case of exiting the NFE, the household may face a barrier to exit such as investments made in non-transferable fixed assets, regulatory burdens and other closure costs that may arise from contract contingencies with suppliers or buyers. These costs may in turn be a function of location specific factors like the investment climate and existence of industrial clusters. For example, the cost of exit in industrial clusters may be lower due to a low level of investment in specialized activities and existence of "deeper markets for specialized assets" (Caves and Porter, 1977). Indicators of the investment climates like the regulatory burdens, the property rights and contract enforcement may also govern the transaction costs of liquidating a business. Furthermore, exit barriers can arise from household specific characteristics that can affect the bargaining power among household members in terms of deciding whether to terminate or continue the business. The bargaining power can be reflected by the social status of household members that can be captured by the age, gender and schooling of the main operator of the business.

The present value of income from the NFE for an incumbent household will then depend on the trade-off between the costs that the household will incur upon exiting and the profit that it will earn if it continues operating the NFE. The profit that the enterprise will earn in turn depends on the price of outputs and inputs of the NFE which are also a function of location specific factors. In addition to location specific factors, enterprise specific factors can also affect the profitability of the enterprise like the size of the enterprise, experience gained during business, the type of operation, etc. Given these, the household will decide to exit the NFE if the present value of income from the NFE is strictly less than the extra income that can be earned if the household had to engage only in the agricultural activity (equation 9).

$$PV_{B,i}^{E} < PV_{i}^{E} - PV_{A,i}^{E}, \qquad (9)$$

where, PV^{E} is the present value of an incumbent household.

If we follow the same formulation as used for the entry decision, the probability of exiting a NFE will then become a function of household specific characteristics (H_i), enterprise specific factors (E_i), fixed inputs of capital and labor (Z_i), location specific factors (N_l, I_l), and exogenous shocks affecting agricultural output (φ_t).

4.3 Data

4.3.1 General Information

Data for this study is obtained from the Rural Investment Climate Survey (RICS) conducted by the World Bank together with the Central Statistical Authority of Ethiopia during December 2006 and January 2007. The survey has two parts where the first part contains more general questions on 14,000 households and 3,500 enterprises in four regions of Ethiopia, namely Amhara, Tigray, Oromia and SNNP. The second part of the survey contains a more detailed information only for Amhara. This part of the survey covers 2,900 households, 760 enterprises and 118 communities from 4 different zones of Amhara, covering almost one-half of Amhara's population of 18 million. The empirical analysis is based on the survey collected only for Amhara due to the availability of detailed information that are relevant for our analysis and because enterprise information can also be matched with household and community level characteristics. In the enterprise survey, information is collected on different forms of non-farm activities that include the manufacturing, trade and service sectors. In addition to the RICS, the 2002/03 Cottage/Handicraft Manufacturing Industry survey and the 2002/03 Large and Medium Scale Manufacturing Establishments Survey, both collected by the CSAE are used to calculate location specific variables.

Studies suggest that the benefits of clustering would best materialize in manufacturing sectors where a number of different specialized producers can operate along the same line of production (Porter, 2000; Nadvi and Barrientos, 2004; Sonobe and Otsuka, 2006b). However, clustering can also occur in the service and trade sectors; examples are the vehicle repair cluster in Ziwani, Kenya (McCormick, 1999) and the horticultural export cluster in Ghana (Jaeger, 2008). Trade and service sectors in rural areas of developing countries also offer a greater source of income and employment than manufacturing activities (Haggblade et al., 2007). From a policy perspective, clustering of trade and service sectors therefore deserve serious attention. However, due to unavailability of data on the service and trade sectors of micro, medium and large scale establishments for calculating location specific variables such as clustering, the current study focuses on manufacturing activities.

4.3.2 Non-farm Enterprises in Ethiopia

The percentage of rural households engaged in NFEs in Ethiopia for the past 8 years has been close to 25%, which is lower compared to the SSA average of 42%. Figure 4.1 shows that there is an upward trend in households' participation from 1998 until 2006/07[18].

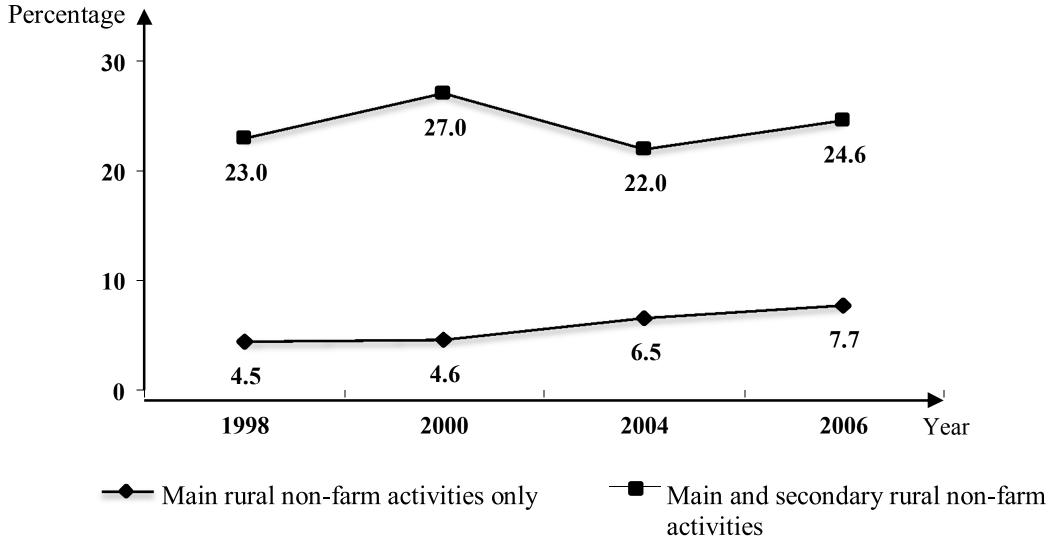
Rural Amhara shows a lower participation of 20% compared to the country's average. Looking at the sectoral composition of NFEs, on the other hand, a relative large percentage of households in Amhara, 43%, are engaged in manufacturing activities (Table 4.1).

There is little growth in NFEs in terms of employment. Only close to 3% of the enterprises in Amhara have experienced positive growth, which is way below the 8% for all the NFEs in the country that have expanded their labor force since start-up. 1% of the enterprises in Amhara have shrunk in size and the rest 96% have experienced zero growth. NFEs in Ethiopia are predominantly small with an average employment of 1.14. A large proportion of NFEs, close to 10%, exit their business permanently within the first three years of their establishments. The total closure rate, which is the sum of the seasonal closure and permanent exit, on the other hand is 25% (Loening et al., 2008)[19].

[18] The figure is compiled using the 1998 and 2004 Welfare Monitoring Survey and the 2006/07 RICS.

[19] The closure rate varies across firms of different sizes. Using a large panel data set for firms in urban Ethiopia, Bigsten and Gebreeyesus, (2007) show that 59% of the medium size firms exit their business permanently within the first 5 years of their establishments, compared to 31% for very large firms.

Figure 4.1 Households' rural non-farm participation (1998/99-2006/07).



Source: CSAE and World Bank, 2008

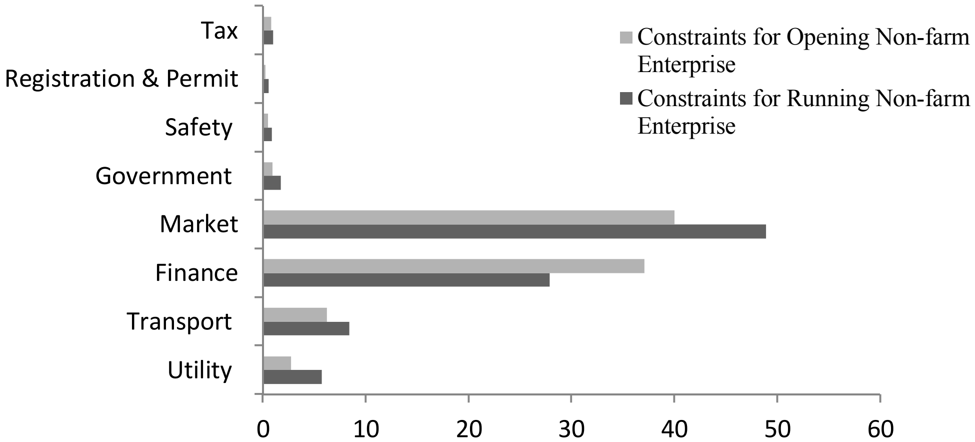
Table 4.1 Participation in NFEs by region and sector (percentage of households)

	Tigray	Amhara	Oromia	SNNP	Total
Participation Rate					
Households owning NFE	22	20	23	37	25
Sectoral Composition					
Manufacturing	30	43	35	32	36
Trade	56	41	52	58	51
Service	14	16	13	11	13

Source: Loening et al., 2008.

There are various constraints that affect NFEs both at start up and during operation. As can be seen in Figure 4.2, access to market both in terms of distance and difficulty of obtaining information is considered as the major constraint both for starting a business and during operation. Access to finance is considered to be the second major constraint both for starting and running a business. Access, quality and cost of transportation and utilities such as electricity, telecommunication, water and postal services are perceived to be major obstacles for running a business but they are less an obstacle for starting one.

Figure 4.2 Perceived main constraints for opening and running a NFE (percentage of households who responded accordingly).



Source: Authors compilation using the 2006/07 RICS.

Very few households perceived government related obstacles such as corruption, uncertain economic policy and restrictive laws and regulations and safety issues such as criminality, theft and lawlessness as major problems for opening and running a business. A much lower response is also found for constraints related to the time and cost of registration and obtaining permits and taxation. This is not surprising given the small size of NFEs in many parts of Ethiopia that are often left unregulated and operate as informal businesses.

4.4 Empirical Model and Variables

Determinants of Entry and Exit of Households into and from Non-farm Enterprises

Following the theoretical framework in section 4.2, we look at the impact of household and enterprise specific characteristics, location specific factors, household's endowment of capital and labor and exogenous shocks in determining the entry and exit of households into and from NFEs. Because we only have cross-section data, we cannot calculate the entry and exit rates of enterprises over time. Instead, we use the responses in the survey in order to capture whether households have entered or exited a NFE in recent times. In the survey, households were asked whether they own a NFE and if yes, in which year they have started the enterprise. Similarly, those who own an enterprise were asked whether they have quitted a NFE. If they have quitted a NFE, they were further asked in which year they have done so. Based on these responses, we construct dummy variables for entry and exit. Entry into a NFE takes a value of one if a household has started a NFE in the past four years of the time of the survey and zero if the household has not started a NFE at all. Similarly, exit from a NFE has a value of one if the enterprise has been stopped in the past four years of the time of the survey and zero if the NFE is still operating at the time of the survey. Following this, we formulate the following probit models; one for the entry decision and another for the exit decision where the dependent variables are dummies for the entry and exit of households into and from NFEs respectively.

$$prob(entry) = \theta_1 H_i + \theta_2 Z_i + \theta_3 N_l + \theta_4 I_l + \theta_5 \varphi_t + \nu, \quad (10)$$

$$prob(exit) = \gamma_1 H_i + \gamma_2 Z_i + \gamma_3 E_i + \gamma_4 N_l + \gamma_5 I_l + \gamma_6 \varphi_t + \xi, \quad (11)$$

where the θ's and γ's are the corresponding parameters to be estimated for the entry and exit decision models respectively. ν and ξ are the error terms of the probit regressions of the entry and exit decision models respectively.

We use information on the entry and exit decisions of households only for the past four years in order to be able to match the information with enterprise and household specific explanatory variables that are available for the year of the survey, 2006/07. This is done under the assumption that most of the enterprise and household specific characteristics did not show a significant change in the past four years of the time of the survey.

As indicators of household characteristics (H_i) that can affect household's entry and exit decisions, we use gender, age, schooling and immigration status of the household head. Labor availability and capital endowment of a household (Z_i) are indicated by household size and wealth of a household respectively. The wealth of a household is captured by a dummy that has a value of one if the roof of the household is made from iron sheet and zero otherwise. In addition to the wealth indicator, we use the percentage of household income from non-agricultural sources such as remittances, government transfers, wages and salaries from off-farm employment and pensions, insurance, etc.

Enterprise specific factors (E_i) used only in the exit decision model include the size of the enterprise, which is measured by the number of workers and experience as captured by the number of years since the establishment of the business. Whether the enterprise is a cottage industry or the operation is performed in a separate workspace outside of the entrepreneur's home is also used as additional enterprise specific factor. NFEs in SSA are often seasonal and are performed to compensate agricultural income. Hence, we use a dummy that has a value of one if the operation of the NFE is seasonal and zero otherwise.

As a measure of clustering (N_l), we construct an index in order to measure the concentration of enterprises in a certain location (l). The location quotient that quantifies how concentrated a certain sector is in a given location compared to a larger geographic unit, is one of the widely used measures of clustering (O'Donoghue and Gleave, 2004). The location quotient for a certain manufacturing sector is calculated for the most detailed spatial unit possible, the district, by using zone, which is the higher spatial unit next to a district, as a reference point.

$$LQ_{di} = (H_d/M_d)/(H_Z/M_Z), \tag{12}$$

where LQ_{di} is the location quotient of a certain manufacturing sector i at district d; H_d is employment of sector i at district d; M_d is total manufacturing employment at district d; H_Z is employment of sector i at zone z and M_Z is total manufacturing employment at zone z.

Here total manufacturing employment includes employment in micro, medium, and large-scale manufacturing sectors. The 2002/03[20] Cottage/Handicraft Manufacturing survey and the 2002/03 Large and Medium Scale Manufacturing Establishments Survey, both collected by CSAE are used for calculating the location quotient at district level.

The response for the entry decision of households, which is obtained from the household survey does not specify the type of activity that the household has decided to engage in. The information provided in the survey is rather general asking each household whether it has started any kind of NFE or not. Because of this, we are unable to construct a concentration index for a specific sector in the entry decision model. Rather, we construct a concentration index for all types of the already established micro enterprises in a certain district by taking zone as a reference point. For the exit decision, however, we have detailed information about the types of manufacturing activity that each enterprise had been engaged in. Hence, the concentration index for the exit decision model is calculated for each type of manufacturing sector at district level. Depending on the types of the manufacturing sector, one district may therefore have more than one concentration index where each enterprise in a district is then assigned an index according to the type of sector that it is engaged in.

In addition to the concentration of micro enterprises, we also calculate the concentration of large manufacturing firms at zonal level using the same technique, the location quotient. This is in order to see if the externalities that surrounding large firms may have an effect on household's entry and exit decisions into and from NFEs. Small producers may benefit from concentration of large firms through inter and intra industry benefits such as information spill-over, technological externalities, availability of a pool of skilled workers, and existence of common services such as research and training centres, government and regulatory institutions, and banking services (Krugman, 1991; Fujita and Thisse, 1996). On the other hand, large firms may pose a challenge for the smaller ones if they are competing

[20] the 2002/03 survey data are used for calculating clustering in order to make the correlation inferable with the dependent variables that are also measured for the past four years of the time of the survey.

for the same market. The 2002/03 Large and Medium Scale Manufacturing Survey collected by CSAE is used to calculate the concentrating index for large firms.

In order to capture the investment climate of a certain location (I_l), we use information from the 2006/07 RICS to capture road access and availability of credit services in nearby locations, various government related policies and regulations and the safety of the community. To capture the road access and credit services in nearby locations, we use the average distance in hours to reach the nearest all-weather road and a micro finance institution (MFIs) respectively. The average distance is measured for each enterprise. Travel time in hours instead of physical distance in kilometres is used in order to capture the quality of the road.

As further indicators of the investment climate, we use governance and safety of a community. In the RICS-Amhara community survey, knowledgeable community residents and leaders such as village headmen, religious chiefs and long-term residents were addressed with different indicators of governance and safety and asked if they would consider these indicators as being a major problem, somewhat a problem, a minor problem or not a problem at all for establishing and expanding a business in their community. Regarding governance, they were asked about corruption, uncertain economic policy and restrictive laws and regulations. Regarding safety, they were asked about criminality, theft and lawlessness in their community. Based on these responses, we construct an index for governance and safety for each community leader in each district. The index ranges from 0 to 1, where an increase indicates a rise in the seriousness of governance or safety issues being major problems for establishing and running a business as perceived by each community leader. We then took the median value of the responses of the different community leaders to come up with one index for each district.

One of the most frequently noted exogenous factors affecting agricultural income and hence a household's diversification decision is rainfall variability. In order to capture rainfall variability (φ_t), we use NOAA Climate Predication Center's African Rainfall

Climatology Data obtained from the World Bank. In the data, rainfall anomalies for each month and each district were calculated for the years 1995 to 2006. From the monthly anomalies, annual anomalies are generated for each district. The annual rainfall anomaly is defined as the deviation from the 12 year rainfall average (1995-2006) and can have both positive and negative values. The district level annual rainfall anomaly is then used to generate an absolute annual rainfall anomaly for each household one year previous to the start of a business and one year previous to the closure of a business for those who have opened and exited a NFE respectively[21]. For those who have not opened and exited a NFE, we use the 2002 absolute rainfall anomaly[22].

As an additional control variable, a rural town dummy is used in both probit models in order to capture all kinds of externalities that towns may provide. Dummies for the different manufacturing activities are also included in the exit regression to indicate for possible sectoral variations.

Impact of Entry and Exit into and from Non-farm Enterprises on Household's Well-being

Well-being of a household is measured using three different indicators. The first one is total household income, which is the sum of agricultural and non-agricultural income. The second measure of well-being is an index that captures the food security status of a household due to various exogenous shocks. In the household survey of the RICS, households were asked whether they have experienced food shortage due to various exogenous shocks like drought, flooding, price variability, and illness and death of a household member. The questions were asked for each household for four consecutive years from 2003 until 2006. Based on this, we construct an index of food shortage for the year 2006. The index ranges from zero to three, zero being no food shortage and three being the highest level of food shortage. The third measure is the ability of a household to

[21] Because we don't have information on the actual amount of rainfall in each district, we couldn't calculate the coefficient of rainfall variation for the 12 year period for which the data is available, as is commonly used in other studies.

[22] The 2002 absolute rainfall anomaly is used for households that have not opened and exited a NFE because the whole analysis of the paper is based on households that have entered or exited a NFE in the past four years of the time of the survey.

raise enough money in case of emergency, which is captured by a dummy that has a value of one if a household responded as being able to raise 100 birr in the case of emergency and zero, otherwise.

To take into account the bias that may arise from self-selection of households in their decision to enter and exit NFEs, we use propensity score matching (PSM) to look at the impact on households' well-being. PSM allows us to match households that share the same pre-treatment observable socio-economic characteristics with the exception of either or not entering and exiting a NFE (Heckman et al., 1997).

The main pillars of PSM are the individuals (household), the treatment (entering into and exiting from a NFE) and the potential outcome of the treatment (household's well-being).

Let $D_i \in \{1,0\}$ be an indicator whether household i has received a treatment or not. The propensity score $\mathrm{P}(X)$ is defined as the conditional probability of receiving a treatment given pre-treatment characteristics as:

$$\mathrm{P}(X) \equiv prob\left(D_i = \ \middle| X\right) = E\left(D_i \middle| X\right), \tag{13}$$

where X denotes a vector of pre-treatment characteristics and E is the expectation operator. The propensity score can be predicted with either a logit or probit model under the assumption of a normal or logistic cumulative distribution respectively. Once the propensity scores are generated, the treatment effect can then be calculated by selecting households that are 'closest' in terms of propensity score as a match.

The most common estimate of treatment effects in the evaluation literature is the average treatment effect on the treated. If the potential outcome of the treatment, which is household well-being, is denoted by $Y_i(D_i)$, then the average treatment effect (ATT) is defined as;

$$ATT = E\left(T \mid D = 1\right) = E\left(Y(1) \mid D = 1\right) - E\left(Y(0) \mid D = 1\right), \tag{14}$$

where $E\left(Y(1) \mid D = 1\right)$ is the expected outcome for those households that have actually received a treatment, in this case those that have entered or exited a NFE, and $E\left(Y(0) \mid D = 1\right)$ is the counterfactual for the treated, which estimates what the outcome would be if those households that have in fact received a treatment do not do so.

An important assumption of PSM is the conditional independence assumption (CIA), which states that the set of pre-treatment observable characteristics that are included in the matching should determine both the probability of receiving a treatment (entering into and exiting from NFEs) and the outcome of interest (household well-being); that is $(Y_0, Y_1) \perp D \mid X$, denoting the statistical independence of (Y_0, Y_1), conditional on pre-treatment observable characteristics, X (Heckman et al., 1997).

Given that the CIA holds, the PSM estimate for the ATT can be written as:

$$ATT_{PSM} = E_{\mathrm{P}(X \mid D=1)}\left\{E\left[Y(1) \mid D = 1, \mathrm{P}(X)\right] - \left[Y(0) \mid D = 1, \mathrm{P}(X)\right]\right\} \tag{15}$$

In order to eliminate outliers that have very high and very low propensity scores, the matching should be restricted to the area of the Common Support in the sample, which can be done by dropping the treatment observations at which the propensity score density of the control observation is the lowest (Sianesi, 2004). To be effective, matching should also balance observable explanatory variables across treated and non-treated groups. For this, a balancing test is performed after the match. This test can check the quality of the match by assessing the extent to which differences in the pre-treatment observable characteristics between treated and non-treated groups have been eliminated.

4.5 Empirical Results

4.5.1 Determinants of Entry and Exit of Households into and from Non-farm Enterprises

The marginal effects of the probit regression for the entry decision model are presented in column II and III of Table 4.2. In column II, almost all household head characteristics included in the model, except for the immigration status, play a role in the entry decision. Households with young and more educated heads are more likely to start a NFE. Female headed households are also more likely to start a NFE. High female participation into NFEs may imply the lack of alternatives for women in other domains, especially agriculture, while men often can exploit profitable market opportunities between complementary activities of non-farm works and agriculture (Loening and Mikael, 2009).

With regard to labor endowment, households with a large number of household members are more likely to start a NFE, which may indicate the existence of 'surplus' labor that can easily be shifted from one activity to the other. In order to see which age cohort of household members is more important for the entry decision, we formulate four different age groups as indicated in column III of Table 4.2. Accordingly, it is found that households having more members in the age cohort of 6 to 15 years old are more likely to start a NFE. This may imply the importance of child labor in the entry decision where either children may directly work in NFEs or engage in agricultural and other house works, the latter allowing other household members to have more time to allocate to NFEs.

Households whose roofs are made from iron sheets are more likely to start a NFE. Similarly, households with a large share of income from non-agricultural sources have a high probability of starting a NFE. This result may imply that alternative income sources other than agriculture can help households to better smooth-out the uncertainty regarding agricultural performance, giving them more incentives to invest in NFEs.

As expected, the concentration of micro enterprises engaged in manufacturing activities in the same district increases the probability of starting a NFE. The concentration of big manufacturing firms in the same zone also increases the probability of starting a NFE. It is interesting to see that the effect of the concentration of micro enterprises in increasing the probability of entry is 23% higher than that of the concentration of big firms. This may imply that the specialization and external economies of scale arising from clustering of micro enterprises that are engaged in similar line of production are more important for households' entry decisions than those arising from big firms.

Among the various indicators of the investment climate, we find a significant effect for access to a road where the further away households are located from an all-weather road, the lower is the probability of starting a NFE. Similarly, households located outside of rural towns are less likely to start a NFE. These findings indicate the importance of reduction in remoteness through improved transportation system for market integration in rural areas (Rijkers and Söderbom, 2010). The availability of micro finance institutions (MFIs) in nearby locations has no significant effect on the entry decision of households. This may be because the importance of MFIs has been substituted by the existence of industrial clusters, which through specialization and division of labor can reduce the required capital to start a business, enabling households to use their capital endowment for investment without necessarily being credit constrained (Huang et al., 2008; Ruan and Zhang, 2009, Ali et al., 2010). In a similar study in rural Ethiopia, Ali and Peerlings (2011a) also find that micro-enterprises are more likely to cluster further away from MFIs, possibly due to the substitutive role played by industrial clusters in easing the financial constraints of entrepreneurs. High rainfall variability, as is captured by absolute annual rainfall anomaly, increases the likelihood of starting a NFE. This is consistent with the findings of other studies in Africa where high rainfall variability pushes households to diversify beyond agriculture often as an ex-ante income smoothing strategy (see for example Rose, 2001, Haggblade et al., 2007).

Table 4.2 Marginal effects of probit regression for the probability of entry and exit into and from a NFE.

	Probability of entry		*Probability of exit*
	II	III	IV
Household head characteristics			
Male (d)	-0.10 (0.02)***	-0.10 (0.02 ***	-0.03 (0.01 **
Age	-0.00 (0.00)***	-0.00 (0.00)***	-0.00 (0.00)
Schooling	0.01 (0.00)***	0.01(0.00) ***	-0.00 (0.00)
Immigrant (d)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.02)
Household labor and capital endowment			
Household size	0.01 (0.00)***		
Household size age≤5		0.01 (0.01)	
Household size 6≤age≤ 15		0.01 (0.00) **	
Household size 15<age≤65		0.00 (0.01)	
Household size age> 65		0.02 (0.02)	
Roof iron sheet (d)	0.03 (0.01)**	0.03 (0.01)***	-0.02 (0.02)
Share of non-agricultural income (%)	0.09 (0.02)***	0.09 (0.02)***	-0.03 (0.05)
Enterprise specific factors			
Size of the enterprise (number of worker)			-0.06 (0.02)**
Year since establishment			-0.00 (0.00)
Cottage industry (d)			-0.25 (0.10)**
Activity seasonal (d)			0.01(0.01)
Concentration			
Concentration of micro enterprises in the same district	0.30 (0.09)***	0.30 (0.09)***	-0.02 (0.01)**
Concentration of big manufacturing firms in the same zone	0.07 (0.03)**	0.07 (0.03)**	0.02 (0.03)
Investment Climate			
Governance	0.02 (0.05)	0.02 (0.05)	0.04 (0.05)
Safety	0.04 (0.03)	0.04 (0.02)	0.07 (0.03)**
Distance to nearest all-weather road (hours)	-0.01 (0.00)**	-0.01 (0.00)***	0.01 (0.01)
Distance to nearest MFI's (hours)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)
Exogenous Shocks			
Annual rainfall anomaly	0.003 (0.00)***	0.003 (0.00)***	0.002 (0.00)*
Others			
Rural Town (d)	0.10 (0.03)***	0.10 (0.03)***	-0.05 (0.03)**
No of observation	2437	2437	353
Pseudo R^2	0.211	0.212	0.271

Note: Robust standard errors are reported in parenthesis. (d) is for discrete change of dummy variable from 0 to 1.
Sectoral dummies for different production activities are included in the exit regression but are not reported here because none of them are significant.
* p<0.10, ** p<0.05, *** p<0.01.

Marginal effects of the probit regression for the exit decision model are reported in Column IV of Table 4.2. Although female headed households are more likely to open a NFE as indicated in the entry decision model, they are more likely to exit their business. The lack of alternatives for many female entrepreneurs in rural parts of Africa often result in them being engaged in less profitable activities that require little training and skills (Loening and Mikael, 2009), which may have resulted in high exit rates. Using the same dataset on rural NFEs, Rijkers and Söderbom, (2010), also find that female owned enterprises have a lower value added per unit of labor than their male counterparts.

Other household head characteristics, both in terms of demographic factors and endowments,[23] do not play a significant role on the exit decision. Enterprise specific factors, on the other hand, are rather important where we find that large enterprises and those operating in their homes are less likely to exit. Similar evidences on enterprise size and location of operation are also found for micro enterprises operating in other African countries of Swaziland and Zimbabwe (McPherson, 1995).

Enterprises operating in districts where there is clustering of other micro enterprises that produce similar and closely related goods have a lower probability of exit than those operating in isolation. Similarly, NFEs operating in rural towns are found to have a lower probability of exit, which may point to the importance of market linkages and external economies of scale in cities for the survival of micro enterprises. Using a similar data set, Rijkers and Söderbom, (2010) also find that enterprises located in rural towns have a higher value added per unit of labor than those located in remote rural areas.

With respect to the different indicators of the investment climate, lack of safety in a community poses a threat for the survival of NFEs. The Enterprise Survey Data compiled by the World Bank on 125 different countries show that a relatively large proportion of small firms in Ethiopia (close to 12%) identify crime, theft and disorder as a major constraint for their business compared to 8% of large firms. In addition, the percentage of

[23] Household size is not included in the exit regression because it is highly correlated with the size of the enterprise, which is measured by number of workers.

small firms in Ethiopia that pay for security is rather high; 54% compared to 49% for all the low income countries in the world. Although we lack further evidence about the real causes of conflict, criminality, theft and lawlessness in rural Amhara; the results of this study indicate that safety could be one of the bottlenecks in the region's, if not necessarily the country's, investment climate. However, this result should be interpreted with caution because the measures for safety are based on subjective responses from district level community leaders.

Just as high rainfall variability triggers entry into NFEs, is it also found to increase the probability of exit. This may be due to a decline in local demand for non-farm products following high rainfall variability, which could influence farmers' income negatively. Since the main customers of non-farm products in rural areas are farmers, (Rijkers and Söderbom, 2010); the decline in local demand could result in closure of NFEs.

4.5.2 Impact of Entry and Exit into and from Non-farm Enterprises on Household's Well-being

There are different matching methods to calculate the average treatment effects in the evaluation literature. The one used in this study is a kernel matching method, which associates the outcome of the treated household with the matched outcome that is given by the kernel-weighted average of all the non-treated households. Since the weighted average of all the non-treated households is used to construct the counterfactual outcome, kernel matching has an advantage of lower variance because more information is used (Heckman et al., 1998). A kernel function can take many forms. The matching results reported in Table 4.3 are using the Epanechinikov kernel functional form.

The results of the PSM are reported in Table 4.3. Households that have started a NFE have on average 2554.64 birr (290.96$)[24] more annual income than those who have not opened a NFE. Similarly, opening a NFE results in a significant reduction of food shortage.

A similar analysis for exit in Table 4.3 show that, households that have exited have on average 935.99 birr (106.61$) less annual household income than those who have not exited their business. With regard to other measures of well-being, however, we do not find a significant result.

The results of the matching quality are reported in Table 4.4. Column I and II show the results of the chi-square test for the joint significance of covariates used in the probit model before and after the match using the three measures of well-being (Sianesi, 2004). The chi square test after the match for the entry decision model confirms that all the covariates in the probit model are not jointly significant with prob>$\chi 2$ = 0.46 for the matches performed on all the three measures of household well-being. Another measure used to confirm the quality of the match is the mean bias reduction after the match (Rosenbaum and Rubin, 1985). As reported in column V, the absolute bias reduction of the covariates after the match in the probit model of the entry decision lies way below the 20% level of bias suggested by Rosenbaum and Rubin (1985). For the exit decision model, the chi-square tests after the match in Column II indicate that the covariates of the probit model are not jointly significant with prob>$\chi 2$ = 0.88 for all the three measures of household's well-being. The mean absolute bias reduction of covariates after the match is also below the suggested 20%. The matching quality tests for the entry and exit models suggest that the matching procedures have performed well in terms of avoiding systematic difference in the distribution of pre-treatment observable covariates included in the PSM between treated and non-treated groups.

[24] The average exchange rate for the year 2006 was 1 $ = 8.78 Birr.

Table 4.3 Treatment Effects : Kernel Matching

Treatment	Outcome indicators	ATT	Treated On support	Treated Off Support	Controlled On Support	Controlled Off support
Entry	Total household income	2554.64 (520.54)***	290	-	2147	-
	Food shortage	-0.09 (0.04)**	290	-	2147	-
	Able to raise money in case of emergency	0.04 (0.03)	290	-	2147	-
Exit	Total household income	-935.99 (472.11)**	30	1	322	-
	Food shortage	0.18 (0.16)	30	1	322	-
	Able to raise money in case of emergency	-0.10 (0.10)	30	1	322	-

Note: the standard errors are reported in parenthesis and are computed after bootstrapping 50 times.

Table 4.4 Indicators of matching quality before and after the match for the three measures of well-being using Kernel Matching

	I	II	III	IV	V
Treatment	p-value[a] (unmatched)	p-value[a] (matched)	Mean[b] absolute bias (unmatched)	Mean[b] absolute bias (matched)	Absolute bias reduction
Entry	0.00	0.46	44.29	8.87	79.97
Exit	0.00	0.88	33.19	18.59	43.98

[a] *p*-value of likelihood ration test ($Pr > \chi^2$)
[b] absolute bias (in percentage) is calculated as the difference of sample mean of outcome variable of the treated and non-treated groups times the square root of the average of the sample variance of outcome variable of the treated and non-treated groups (Rosenbaum and Rubin, 1985).

To check if the above results of the match are robust to different kinds of matching methods, a sensitivity analysis is performed by using a different matching algorithm, a Radius Matching[25]. The results of the match are presented in Table 4.5 and 4.6. The findings confirm that the matching results are quite robust and are not sensitive to the different matching algorithms used.

[25] In Radius Matching each treated unit is matched with the control unit whose propensity score lies within a specified neighborhood (radius).

Table 4.5 Sensitivity of matching algorithms: Radius matching

Treatment	Outcome indicators	ATT	Treated		Control	
			On support	Off Support	On support	Off support
Entry	Total household income	2717.14 (558.78)***	290	-	2147	-
	Food shortage	-0.10 (0.04)**	290	-	2147	-
	Able to raise money in case of emergency	0.04 (0.03)	290	-	2147	-
Exit	Total household income	-946.12 (440.01)**	30	1	322	-
	Food shortage	0.19 (0.14)	30	1	322	-
	Able to raise money in case of emergency	-0.09 (0.09)	30	1	322	-

Note: the standard errors are reported in parenthesis and are computed after bootstrapping 50 times.

Table 4.6 Indicators of matching quality before and after the match for the three measures of well-being using Radius Matching.

Treatment	p-value[a] (unmatched)	p-value[a] (matched)	Mean[b] absolute bias (unmatched)	Mean [b] absolute bias (matched)	Absolute bias reduction
Entry	0.000	0.11	44.29	12.12	72.63
Exit	0.000	0.56	33.18	22.89	31.01

[a] *p*-value of likelihood ration test ($Pr > \chi^2$)
[b] absolute bias (in percentage) is calculated as the difference of sample mean of outcome variable of the treated and non-treated groups times the square root of the average of the sample variance of outcome variable of the treated and non-treated groups (Rosenbaum and Rubin, 1985).

Although the above results of the PSM indicate that biases that may arise from observables are controlled for, it might be difficult to infer a causal relationship between diversification and well-being as there could still be some unobservable factors that exert certain effects both on NFE participation and household's well-being. For example, it is possible that both well-being and NFE participation is driven by another external force such as "migration patterns and technological change in agriculture" (Lanjouw, 2007, pp 56). In addition, farm and non-farm earnings can reinforce each other, which could then influence household's well-being through indirect channels such as tightening of the agricultural labor market or raising demand for agricultural products, etc. (Janvry, 1994; Loening and Mikael, 2009).

4.5.3 Sensitivity Analysis

Agricultural income of households, which is part of the total household income used as one of the well-being indicators in this study is based on mainly marketed agricultural products. There could also be non-marketed agricultural products that households can use for own consumption. Total household income should therefore include the imputed values of non-marketed agricultural products. Failure to do so can understate total household income, especially for those households who have not opened NFEs and rely on agricultural income as their main income source.

In the RICS we do not have separate information on non-marketed agricultural products and their values. Therefore, we cannot directly correct for non-marketed agricultural products in our measure of total household income. Instead, we have information on values of food items that have been consumed by each household. These food items can either be produced by the household or purchased from the market. Based on this information, we perform a sensitivity analysis where we investigate the impact of entry and exit decisions on the value of food items consumed by each household in the past 12 months of the time of the survey. Food items cover the largest share of total household expenditure in rural households in SSA and most of the non-marketed agricultural products are used for consumption purposes (Delgado et al., 1998). The sensitivity analysis on values of food items will therefore allow us to capture the effect on household income that is not affected by the exclusion of non-marketed agricultural products. The results of the PSM are presented in Table 4.7 and 4.8. We find a significant increase and decrease of the value of food items consumed due to entry and exit respectively.

Table 4.7 Treatment effects using values of food items consumed as an outcome variable: Kernel Matching

Treatment	Outcome indicators	ATT	Treated On support	Treated Off support	Control On support	Control Off support
Entry	Total value of food items consumed	301.52 (125.14)**	290	-	2147	-
Exit	Total value of food items consumed	-630.81 (233.28)***	30	1	322	-

Note: the standard errors are reported in parenthesis and are computed after bootstrapping 50 times.

Table 4.8 Indicators of matching quality before and after the match using values of food items consumed as an outcome variable: Kernel Matching

	I	II	III	IV	V
Treatment	p-valuea (unmatched)	p-valuea (matched)	Meanb absolute bias (unmatched)	Meanb absolute bias (matched)	Absolute bias reduction
Entry	0.00	0.46	44.28	8.86	79.80
Exit	0.00	0.88	33.18	18.59	43.97

[a] p-value of likelihood ration test ($Pr > \chi^2$)
[b] absolute bias (in percentage) is calculated as the difference of sample mean of outcome variable of the treated and non-treated groups times the square root of the average of the sample variance of outcome variable of the treated and non-treated groups (Rosenbaum and Rubin, 1985).

4.6 Conclusions and Discussion

This paper examines how clustering affects the entry and exit decisions of farm households into and from NFEs in rural Ethiopia. It is found that the existence of clusters of micro enterprises operating in the same district increases the likelihood of farm households to start a NFE. Similarly, clustering of big manufacturing firms in the same zone is found to increase the likelihood that farm households start a NFE, although its effect is less than that of clustering of micro enterprises. This may imply that specialization and external economies of scale arising from clustering of micro enterprises are more important for households' entry decisions than those arising from big firms. NFEs operating in clusters are also found to have a lower probability of exit than those operating outside of clusters.

The study further investigates the impact of entry and exit into and from NFEs on household's well-being by using total household income, the food security status of a household and its ability to raise enough money in case of an emergency, as indicators. Using propensity score matching to account for selection bias on observables, it is found that, entry into NFEs significantly increases household income and their food security status. Exit from NFEs, on the other hand, is found to significantly reduce households' income. The results of the PSM are also found to be robust for different matching algorithms used.

The findings of this study indicate that the growing interest of policy makers to promote NFEs in rural areas of Africa should take into account the importance of industrial clusters that could help to reduce the various transaction costs that entrepreneurs may face both when establishing and expanding their businesses. While the constraints faced by rural NFEs in Africa are heterogeneous, lack of market integration remains to be the most important one (Loening and Mikael, 2009). The results of this study show that clustering could be one way where market integrations can be enhanced by helping increase competition and smoothing out market failures such as in credit markets. Policies seeking to address poverty in Africa should also consider the potential contributions of rural NFEs on households' well-being. Although we find that participating in NFEs and well-being are positively correlated, we are unable to disentangle the causality, and hence cannot conclude that rural NFEs necessarily lift the poor out of poverty.

A caveat of this study is the lack of panel data, which restricts the possibility of looking at the dynamic impact of clustering on starting-up businesses. Furthermore, the lack of detailed data on other regions of Ethiopia has made the analysis to focus mainly on Amhara, which has a relatively lower NFE participation rate. Lack of location specific information on trade and service sectors has also limited the study to only the manufacturing sector. Despite these shortcomings, the results of this study show the role of clustering as one way of enhancing rural development by fostering entrepreneurship.

CHAPTER 5

Ethnic Ties in Trade Relationships and the Impact on Economic Performance: The Case of Small-Scale Producers in the Handloom Sector in Ethiopia[♣]

Abstract: *This paper analyzes the importance of ethnic ties in trade relationships of small-scale producers in the handloom sector in Ethiopia using both a non-parametric and a parametric statistical method. It is shown how various socio-economic characteristics of producers lead to ethnic ties with traders. It is also shown that ethnic ties affect the performance of producers negatively. Apparently the positive effect of ethnic ties, through the reduction of transaction costs arising from market imperfections, does not outweigh the negative effect of closed social networks.*

Keywords: ethnic ties, trade, transaction cost, small-scale producers, Ethiopia.

[♣] Paper by Merima Ali and Jack Peerlings, *Journal of Development Studies* (2011), 47(8): 1241-1260.

5.1 Introduction

In the presence of transaction costs associated with market imperfections and in the absence of an effective legal system, trade relationships of small-scale producers in developing countries are often based on trust that in turn is based on local group cohesion and common identity such as ethnic ties (Annen, 2001; Fafchamps, 2002; Bowles and Gintis, 2004). Such bonding social capital manifested through ascribed trust to members of one's own ethnic group helps to reduce the costs of producers in searching and reaching traders, and facilitates contractual enforcement due to the availability of low-cost information about one's trading partner (Bowles and Gintis, 2004; Alesina and La Ferrara, 2005; Knorringa and van Staveren, 2006). Ethnic ties can also help traders to screen potential business partners and grant credit for producers, especially in the initial phase of their business (Fafchamps, 2000; Fisman, 2001).

In addition to reducing transaction costs, ethnic ties may also play an important role in providing social protection. Social networks based on a common identity may give a sense of security to vulnerable producers who tie themselves to traders that offer short-term stability through a 'patron-client' relationship (Wood, 2003). This kind of relationship might prevail on survival-oriented and risk-averse producers with limited alternatives other than subordinate transaction with traders.

While ethnic homogeneity can positively impact business outcomes by reducing transaction costs, and is important for survival and access to various resources, it may also hinder economic performance by limiting access to a wider range of business-related ideas and constrain the ability of producers to respond to 'exogenous developments' (Nadvi, 1999; Annen, 2001; Annen, 2003; Knorringa and van Staveren, 2006; Nooteboom, 2007).

Furthermore, an exclusive social network can restrict the business relationship to only a few agents, who can change the power structure and easily manipulate the exchange process depending on their control over 'power resources' such as information about prices, markets, capital and credit (Nadvi, 1999; Lyon, 2000; Alesina and La Ferrara, 2005). In general, inward-looking social networks can 'insidiously turn from ties that bind to ties that blind' (Grabher, 1993: 24).

Using a rich dataset of small-scale handloom producers operating in clusters in Ethiopia, the purpose of this study is to identify socio-economic factors that determine ethnic ties in contacts between producers and traders. In addition, it analyzes whether ethnic ties positively or negatively affect the performance of producers, in other words whether the benefits of ethnic ties are higher or lower than the costs of having closed social networks.

By unraveling various factors leading to ethnic ties in trade relationships and analyzing the effect on economic performance, this study adds to the growing literature that is exploring the role and impact of social networks on small-scale producers in developing countries (Moore, 1997; Fafchamps and Minten, 1999; Nadvi, 1999; Schmitz, 1999; Lyon, 2000; Nooteboom, 2007).

In Ethiopia, where there are more than eighty languages and as many ethno-linguistic groups, ethnic ties play an important role both in the day-to-day lives of people and in trade relationships. This may particularly be true for the handloom sector, which is characterized by naturally emerged clusters that are dominated by certain ethnic groups with their own language and distinct cultural and social norms. Based on the cultural background of weavers, handloom products also have specific designs distinct to each ethnic group.

Although the sector supports the lives of more than 220,000 people (CSAE, 2003), enterprises are often small in size and most operate in their dwellings using family labor. Those operating in their dwellings are more likely to be isolated from outside markets with limited information about prices and the organization of the market. Given this situation, they have to rely more on localized group cohesion originating, for example, from ethnic ties as a buffer for market imperfections. In addition, enterprises in the sector face financial constraints both when starting up their business and during operation (CSAE, 2003). This has led a large proportion of producers to rely on informal sources of finance such as borrowing from friends and relatives and trade credit (Ayele et al., 2009). Most traders in the sector used to be weavers themselves and often have their close relatives working in the sector, which might further strengthen the social bond and personalized trust between producers and traders. In general, handloom clusters in Ethiopia are not only business agglomerations but also socio-cultural entities where people interact on a personal basis, which could also be reflected in trade relationships.

Such strong social bonds may positively impact business outcomes of handloom producers through, for example, easing credit constraints both when starting up a business and during operation and provision of business related information. Trade credit between producers and traders is found to be widespread in handloom clusters in Ethiopia and help to ease working capital constraints (Ayele et al., 2009). Furthermore, traders in handloom clusters are found to be the main source of information about prices and new techniques of production (Ayele et al., 2009). However, trade relationships based on ethnic ties may also impact the performance of producers negatively either through limited flows of new business related ideas or manipulative power structure on the side of traders who can take advantage of their control over market information.

In this study, we find that recent immigrants and less experienced producers are more likely to be ethnically tied. Ethnic ties are also found to be important for producers operating in remote areas. On the other hand, producers with a wide network of business-related contacts with different traders such as those operating in producers' cooperatives are less likely to be ethnically tied. Ethnic ties in credit provision are also found to lock producers into trade relationships. The impact of ethnic ties on economic performance of producers further reveals that ethnic ties result in lower profits. And the loss in profit due to ethnic ties is found to be higher for immigrant producers.

The remainder of the paper is organized as follows. Section 5.2 provides a brief review of the data while section 5.3 presents the empirical model. Section 5.4 describes the results and the conclusions are outlined in section 5.5.

5.2 Data

5.2.1 Data Collection

The study uses data collected on handloom producers by the International Food Policy Research Institute (IFPRI) in collaboration with the Ethiopian Development Research Institute (EDRI) from March until May 2008. The survey covered 486 handloom producers in nine clusters, three of which are found in the capital city, Addis Ababa, and the rest in the Gamo zone in the Southern Nations Nationalities and Peoples (SNNP) region. These two regions have been selected because of their large concentration of handloom establishments in proportion to other manufacturing activities (Ayele et al., 2009). Sample units were selected based on the proportion of the handloom establishments in the different clusters (Ayele et al., 2009). Of the total handloom producers covered in the survey, 40 percent are from urban areas and 60 percent from rural areas. In the survey, producer-specific information like education level, gender and experience are included. These are supplemented by information regarding horizontal and vertical networks through cooperation among producers and between producers and traders respectively. Detailed information regarding the ethnicity of producers and traders and the number of traders with which producers have regular contact, and for how many years, is also included. Furthermore, information regarding whether a producer is an immigrant or not and when a producer has migrated to a cluster are included. After discarding observations including incomplete and inconsistent information, this study uses data from 473 handloom producers.

5.2.2 A Characterization of Handloom Producers

This section provides a brief discussion about producers and their ethnic ties with traders based on the surveyed data. In this paper we define the level of ethnic tie as the proportion of traders that are of the same ethnic group as the producer. This is calculated by dividing the number of traders that are of the same ethnic group as the producer by the total number of traders regularly contacted by the producer in the past 12 months of the time of the survey. From this, we classify a producer as being ethnically tied if more than half of the traders that he/she has transacted with on a regular basis are of the same ethnic group as the producer. Otherwise, they are classified as non-ethnically tied. Among the 473 producers, 69.3 percent are ethnically tied and the remaining 30.7 percent are not ethnically tied.

Producers in the survey belong to five ethnic groups. The majority of producers (79.3%) belong to the *Gamo* ethnic group followed by the *Amhara* ethnic group (18.0%), (Table 5.1). Compared to other ethnic groups in Ethiopia, weaving is a predominantly common practice in these two ethnic groups and is a tradition where the distinct designs and knowledge of weaving have been passed from generation to generation. Among the *Gamo* ethnic group, 79.2 percent of the weavers are ethnically tied compared with 32.9 percent in the case of the *Amharas*. The majority of the *Oromos* and *Gurages* included in the survey are not ethnically tied with traders (Table 5.1).

Of the 473 surveyed handloom producers, 217 are immigrants from other towns and regions (Table 5.1). Among the immigrant producers, 57.1 percent are ethnically tied, (Table 5.1). A large proportion, 79.7 percent, of the non-immigrant producers are also ethnically tied, which might be because almost 60 percent of producers in the survey operate in rural areas while the majority of migration occurs in the direction of urban clusters.

There are various marketing channels used by producers to sell their output to traders. Producers were asked to state the first most important marketing channel they use to sell their products. 83.5 percent of producers responded that they sell their products in open markets where they transact with mobile traders who usually travel to the marketplace on certain days of a week to collect finished products in bulk from various producers (Table 5.1). This marketing mechanism is common in rural markets where traders travel from Addis Ababa and other urban towns and collect products which they then channel to consumers in towns like Addis Ababa (Ayele et al., 2009). These urban traders were mostly born and raised in rural areas and have strong social networks and family ties that can enhance trust-based transactions. Of the 395 producers selling their output to traders in the open market, 73.9 percent are ethnically tied (Table 5.1).

Table 5.1 Producers' characteristics

	Total		Ethnically tied producers		Non-ethnically tied producers	
	Freq.	%	Freq.	%	Freq.	%
Ethnic Groups						
Oromo	8	1.69	1	12.50	7	87.50
Gurage	3	0.63	1	33.33	2	66.67
Amhara	85	17.97	28	32.94	57	67.06
Gamo	375	79.28	297	79.20	78	20.80
Others	2	0.42	1	50.00	1	50.00
Migration status						
Immigrant	217	45.88	124	57.14	93	42.86
Non-immigrant	256	54.12	204	79.69	52	20.31
Marketing channel						
Open market	395	83.51	292	73.92	103	26.08
Contractual-based transaction	37	7.82	20	54.05	17	45.95
Street stand shops	24	5.07	9	37.50	15	62.50
'door-to-door' traders	17	3.59	7	41.18	10	58.82
Receiving trade credit from traders						
Yes	197	41.65	146	74.11	51	25.89
No	276	58.35	182	65.94	94	34.06

Selling on a contractual basis is another form of marketing channel. 7.8 percent of the producers sell their output to traders that act as intermediaries for ordering companies, usually exporters (Table 5.1). Since traders act as an important agent in linking producers with contracting companies, the business of producers may depend on the kind of networks they have with traders. According to the survey, almost 54.1 percent of those selling on a contractual basis are ethnically tied.

8.7 percent of producers sell to traders operating in street-stand shops and 'door-to-door' traders that tour enterprises to collect products (Table 5.1).

When we look at the credit relationship between producers and traders, about 41.7 percent of producers have received credit from traders in the past 12 months of the time of the survey (Table 5.1). Credit provision by traders is bound to several conditions; previous successful business with a trader and being a relative of a trader are the major ones according to the survey. Among producers who have received trade credit, 74.1 percent are ethnically tied (Table 5.1).

5.3 Empirical Model and Estimation

5.3.1 Effects of Ethnic Ties on Profitability of Producers

In order to capture the effect of ethnic ties on the economic performance of handloom producers, we use profit[26] as an indicator of performance and compare the average monthly profit of ethnically tied and non-ethnically tied producers. However, simply comparing the profit of ethnically tied and non-ethnically tied producers may result in selection bias since transacting with traders is not a random process. This means that producers with certain socio-economic characteristics might self-select themselves to transact with a member of their own ethnic group. These socio-economic characteristics in turn can affect the profitability of producers.

[26] Profit is defined as value of production minus value of raw materials, operational costs and wage and salaries for paid apprentices, seasonal and temporary workers and paid permanent workers. Opportunity cost of family labor is not included because family labor is assumed to be a fixed input in the short run.

To take into account the bias that can arise from self-selection of producers in transacting with traders from the same ethnic group, we match producers that share the same socio-economic characteristics with the exception of being ethnically tied or not. For this we use a non-parametric statistical method known as propensity score matching (PSM) (Heckman et al., 1997).

The main pillars of PSM are individuals (handloom producers), the treatment (being ethnically tied) and potential outcome of the treatment (profit). Unlike parametric techniques such as OLS, PSM requires no assumption about the functional form between outcomes and covariates. Parametric techniques requiring a functional form may result in biased estimates if the covariate distribution differs substantially between treated and non-treated groups (Eren, 2007). Unlike OLS, PSM also eliminates outliers and helps to achieve a more precise estimation of the treatment effect (Sianesi, 2004). In addition, PSM allows a comparison of the treatment effect before and after the bias that arises from self-selection has been controlled for. However, PSM is only concerned with calculating the treatment effect, and thus omits any information about how other factors might also affect the outcome. OLS, on the other hand, gives additional insight into the effect of covariates other than the treatment. Hence we also estimate the effect of ethnic ties on the profitability of producers by using OLS, and we compare the results with PSM accordingly.

Propensity score matching

Let $D_j \epsilon\ (1,0)$ be an indicator of whether producer j is ethnically tied or not. The potential outcome of ethnic ties is the monthly profit for producer j, which is defined as $\pi_j(D_j)$. The effect of ethnic ties on individual producer j can then be written as:

$$T_j = \pi_j(1) - \pi_j(0) \tag{1}$$

With this specification, however, one cannot observe the counterfactual, that is, the profitability of producer j had he/she not been ethnically tied with traders. To deal with this problem, other producers that share similar observable characteristics, but who are not ethnically tied with traders, will be identified and the average effect on monthly profit, instead of the individual effect, will be computed.

Although there are different ways to estimate the average treatment effect, the one that has received most attention in the evaluation literature is the average treatment effect on the treated, which is defined as:

$$ATT = E(T|\ D = 1) = E[\pi(1)|\ D = 1] - E[\pi(0)|\ D = 1] \qquad (2)$$

where ATT is the average treatment effect on the treated and $E[\pi(1)|\ D = 1]$ is the expected outcome for those producers actually selling to traders of their own ethnic group or that received a treatment, and $E[\pi(0)|\ D = 1]$ is the counterfactual for the treated, which estimates what the outcome would be if those producers that are in fact selling to traders of their own ethnic group do not do so. Since the counterfactual cannot be observed, it should be constructed using producers that do not sell to traders of their own ethnic group but share similar observable characteristics, except for being ethnically tied.

An important assumption of this method is the conditional independence assumption (CIA) which states that the set of observable characteristics that are included in the matching should determine both the probability of being ethnically tied and the outcome of interest (profit); that is $(\pi_0, \pi_1) \perp D|\ v$, denoting the statistical independence of (π_0, π_1) conditional on observable characteristics, v (Heckman et al., 1997).

If all the variables influencing both the probability of being ethnically tied and profitably of producers are not incorporated, then CIA is violated since the impact of ethnic ties will be accounted for by information that is not included in the estimation of the predicted probabilities (propensity scores) (Smith and Todd, 2005).

Given that the CIA holds, the PSM estimate for ATT can be written as:

$$ATT_{PSM} = E_{P(v)|\ D=1}\{E[\pi(1)|\ D = 1, P(v)] - E[\pi(0)|\ D = 1, P(v)]\} \qquad (3)$$

where $P(v)$ is the probability of being ethnically tied based on observable socio-economic characteristics, v.

Once the propensity scores are generated using a probit regression, a producer that is not ethnically tied with traders but is 'closest' in terms of propensity score has to be selected as a match. This is done using the Kernel matching method that associates the outcome of an ethnically tied producer j with the matched outcome that is given by a kernel-weighted average of all the non-ethnically tied producers. Since the weighted averages of all producers that are not ethnically tied are used to construct the counterfactual outcome, kernel matching has an advantage of lower variance since more information is used (Heckman et al., 1998). The weight given to non-ethnically tied producer i is in proportion to the closeness between i and the ethnically ties producer j.

In order to eliminate outliers that have very high and very low propensity scores, the matching is restricted to the area of Common Support in the sample, which is defined by dropping the treatment observations at which the propensity score density of the control observation is the lowest (Sianesi; 2004). To be effective, matching should balance observable explanatory variables across ethnically tied and non-ethnically tied producers. For this, a balancing test is performed after the match. This test is primarily concerned with the extent to which the difference in the observable characteristics between ethnically tied and non-ethnically tied producers has been eliminated.

OLS regression

We estimate the following OLS regression to look at the impact of ethnic ties on the profitability of producers.

$$profit = \alpha_0 + \alpha_1 EthnicTie + \sum_{i=2}^{n} \alpha_i x_i + \varepsilon, \qquad (4)$$

where the dependent variable is the monthly profit of producers, $EthnicTie$ is a dummy that has a value of 1 if more than half of the traders that a producer has transacted with on a regular basis are of the same ethnic group as the producer, and 0 otherwise; α_0 is a constant, α_i are unknown parameters to be estimated; x_i are control variables that affect the profitability of a producer besides ethnic ties; and ε is a random term.

5.3.2 Variables and Hypothesis

In order to capture the impact of ethnic ties on the performance of producers using PSM, observable factors affecting both the probability of receiving a treatment (being ethnically tied) and the outcome of the treatment (profitability) should be controlled for. Following the arguments in section 5.3.1, we estimate the following probit model, which is used to generate propensity scores to match producers.

$$EthnicTie = \sum_{i=1}^{n} \alpha_i x_i + \varepsilon \qquad (5)$$

where $EthnicTie$ is a dummy that has a value of 1 if more than half of the traders that a producer has transacted with on a regular basis are of the same ethnic group as the producer, and 0 otherwise α_i are unknown parameters to be estimated; x_i are explanatory variables; and ε is a random term.

The explanatory variables included in the model are various socio-economic characteristics of producers. We include variables like experience that is measured as number of years in which the owner has been in the handloom business and a dummy that captures whether the producer has migrated from another region to join a cluster or not. We would expect ethnic ties to be more important for less experienced and immigrant producers. Among immigrant producers, we also want to investigate if there is a difference in the importance of ethnic ties between recent and earlier immigrants. For this, we estimate another model for immigrant producers only by using a variable that captures the number of years since the producer migrated to a cluster. We would expect ethnic ties to be more important for recent immigrants and to diminish in importance for earlier immigrants that might have started to earn trust through long-term business relationships.

Ethnic ties become important during trade relationships in the provision of credit. Ethnicity and family linkages can help traders to screen potential business partners and provide capital to producers, especially in the initial phase of their business (Fafchamps, 2000; Fisman, 2001). Anecdotal evidence suggests that this is a common phenomenon in handloom clusters in Ethiopia, where the more successful traders act as guardians to bring their kin members and close relatives from rural areas to work in rural towns and big cities. Not only do these traders provide the newcomers with a place to stay, but they also grant them capital to start their own businesses on the condition that they will pay them back. This condition may oblige handloom producers to continue to trade with their own ethnic group who are not only business partners but also close relatives. But once producers have established more contacts, the credit tie may diminish and family and ethnic linkages may lose their importance. Because we do not have separate information on the amount of starting capital borrowed from traders, we use the total percentage of starting capital borrowed from relatives of handloom producers as a proxy. We expect producers with a large share of starting capital borrowed from relatives to be ethnically tied.

Related to this, we include the value of machinery and equipment as an explanatory variable. On the one hand, if ethnicity and family linkages are important in the provision of credit, especially at the start of the business, producers may have used the trust developed through ethnic networks to borrow more money and invest it in machinery and equipment. Given that there could be a credit tie, these producers might continue to transact with traders of their own ethnic group. On the other hand, those with more machinery and equipment might be producers that already had better alternatives for obtaining credit from other sources such as formal banks or they may even have raised the money from their own savings, which may diminish the importance of ethnic ties.

The wealth of a producer might also be another factor in determining whether he/she attaches more importance to ethnic ties or not. We would expect wealthier producers to have better alternatives than poorer producers when it comes to choosing with whom to trade. For example, wealthier producers may have enough collateral for borrowing money for their business and they can easily go to formal banks instead of relying on ethnic ties. In addition, wealthier producers could invest more in their business and take more risky business decisions that would allow them to have wider networks with various traders. On the other hand, poorer producers might choose ethnic ties as a survival strategy that would help them manage risks by securing small but less variant income (Greenwald and Stiglitz, 1990; Wood, 2003). As an indication of wealth, we use a dummy that captures whether a producer owns a workshop (building) or not.

Besides economic gains when trading with one's own ethnic group, there is also a social component present where producers might simply inherit the business networks of their parents. To capture this effect, we use a dummy if producers are of the second generation or not, in other words whether their parents were in the handloom business before them or not. We would expect second-generation producers to have relatively better information about the business in general and markets in particular as they could have shared the experience of their parents. Hence, second-generation producers might be less likely to be ethnically tied.

In addition to social and economic factors, the size of the enterprise might be important in determining whether a producer attaches great importance to ethnic ties or not. The smaller the enterprise, the smaller the network that the producer might have, and hence, the more likely to sell his/her products to the few traders that the producer is familiar with through ethnic ties. The larger the enterprise, however, the more likely it is that the producer has already established a wide and intensive network with various traders, diminishing the importance of ethnic ties. We use the number of people who are actively working in the

enterprise as an indicator of size, and we expect smaller enterprises to be more likely to be ethnically tied.
Another variable used in the probit regression is a dummy that captures whether a producer is a member of a producers' cooperative or not. We would expect producers that are members of a cooperative to have a large network with traders and to have better bargaining power, thereby diminishing the importance of ethnic ties.

Since producers from the *Gamo* ethnic group are a majority in our survey, it is more likely for *Gamos* to be ethnically tied than producers from other ethnic groups. For this we use a dummy that captures whether a producer belongs to the ethnic majority, *Gamo*, or not. In addition, we also include dummies for the various marketing channels used by producers. We would expect producers transacting with traders in open markets to be more ethnically tied than producers using other marketing channels since open markets are more common in rural and remote areas (Ayele et al., 2009), thus increasing the importance of trust-based transactions with mobile traders.

Instead of using a dummy for urban and rural areas in order to capture regional variation, we use a dummy that depicts the infrastructural facilities available in the various clusters. This is because there is a strong correlation between the regional dummy and the dummy for being a member of a producers' cooperative since most producers operating in cooperatives are found in the capital city, Addis Ababa. As an indicator of infrastructural facility, we use a dummy that indicates whether there is access to electricity or not. There is a strong correlation between the infrastructural dummy and the regional dummy; hence we believe that the infrastructural dummy is a good proxy to capture regional variation. Gender, schooling and age of the producer are also used as control variables.

A shortcoming of PSM is that it only eliminates biases arising from observable variables and it does not control for possible biases that may arise from unobservables, which can simultaneously affect the assignment to treatment and the outcome variable (violation of conditional independence assumption). For example, ethnically tied producers may be less talented than non-ethnically tied producers, which in turn can affect their profitability. There may also be certain cultural beliefs specific to certain ethnic groups that can promote for example capital accumulation through ‘self-denial’ (Moor, 1997). Such beliefs may affect the kind of relationships that producers choose in trade exchanges, which in turn affect their success and profitability. Producers might also be risk-averse as in the case of survival-oriented firms that may rely more on ethnic ties and less upon transactions with ‘intimate others’ (Wood, 2003). This kind of producer may forgo long-term growth and profitability for short-term security by committing to ‘patron-client relationships’ (ibid). In this research we do not have a good measure of risk aversion although wealth of producers, measured in this research by ownership of the workshop, might give some indication. Due to a lack of valid instruments, we could not check if such biases from unobservables exist and thus were unable to control for them.

5.4 Results

5.4.1 Determinants of Importance of Ethnic Ties in Trade Relationships

Table 5.2 shows the marginal effects of two probit regression models; one for all producers in the survey and the second for immigrant producers only. In the model estimated for immigrant producers, there is high correlation between the variables, experience and year since immigration. This is to be expected, since most producers could have migrated to start a business. To avoid multicolliniarity, the variable ‘experience’ is discarded in the second model. In addition, the dummies for access to electricity and owning a workshop/building are discarded in the second model because these variables perfectly predicted the binary dependent variable, ethnic ties.

Less experienced producers are more likely to be ethnically tied in the first model, indicating the importance of ethnic linkages in the provision of information at the start of a business. A similar finding was seen in the surgical instrument cluster in Pakistan, where

ethnic ties and family relationships are important for providing information and a material basis at the start of the business (Nadiv, 1999).
In contrast to what is expected, immigrants in general are less likely to be ethnically tied. This could be because those who chose to migrate are already the more ‘able’ part of the society with wider ambitions and endurance than non-immigrants (Moore, 1997), probably with less preference for ethnic ties. However, in the second model estimated for immigrant producers only, ethnic ties are found to play an important role for recent immigrants, and diminish in importance for earlier immigrants.

In both models, producers with a large percentage of starting capital borrowed from relatives are more likely to be ethnically tied, which might be due to credit ties where producers who cannot pay back are forced to continue to trade with those who have provided them with credit. Such credit ties might result in power asymmetry, where the trade relationship that was once based on ascribed trust will shift to an unequal interaction, with the powerful party having more say in the exchange (Lyon, 2000). This is consistent with the finding that producers possessing a larger value in machinery and equipment are more likely to be ethnically tied. This could be because producers who have once used the trust developed through ethnic networks to borrow more money and invest it in their businesses are now tied in trade relationships due to credit ties.

As expected, those working under cooperatives are less likely to be ethnically tied in both models, possibly due to information and networking facilities generated while working through cooperatives that might diminish the importance of ethnic ties. On the other hand, producers operating in areas where there is no access to electricity are more likely to be ethnically tied. This could be an indication of the remoteness of the cluster so that ethnic ties with traders may become important in reducing risks that are associated with marketing, and facilitate trust in long-distance trades (Ali and Peerlings, 2011a).

Producers that belong to the majority ethnic group (*Gamo*) are more likely to be ethnically tied than minority ethnic groups like *Amharas, Gurages* and *Oroms*. In addition, those producers selling their product in the open markets are more likely to be ethnically tied as expected. In the first model, those transacting on a contractual basis are also more likely to be ethnically tied, although the probability is much lower compared to those selling in open markets.

Table 5.2 Marginal effects¤ from probit regression (standard errors are given in parentheses).

	Marginal effects	
Variables	Whole sample	Immigrants only
Male[d]	0.03 (0.19)	-0.25 (0.22)
Age	0.01 (0.01)	0.01 (0.02)
Age squared	-0.00 (0.00)	0.00 (0.00)
Schooling	0.00 (0.00)	-0.00 (0.01)
Experience	-0.01 (0.00)***	--
Second generation[d]	-0.07 (0.05)	-0.01 (0.08)
Immigrant[d]	-0.11 (0.05)**	--
Year since immigrated	--	-0.01 (0.00)**
Ethnic majority[d]	0.33 (0.08)***	0.43 (0.09)***
Member of producers' cooperative[d]	-0.29 (0.08)***	-0.35 (0.11)***
Starting capital borrowed from relatives (%)	0.001 (0.00)***	0.001 (0.00)*
Open market[d]	0.18 (0.09)*	0.35 (0.13)***
Contract[d]	0.12 (0.07)*	0.21 (0.13)
Number of persons working in the enterprise	0.01 (0.02)	0.01 (0.03)
Current value of machinery and equipment	0.01 (0.00)**	0.01 (0.01)***
Ownership of workshop[d]	-0.12 (0.18)	--
Access to electricity[d]	-0.21 (0.05)***	--
Number of observations	473	217
Prob > chi^2	0.00	0.00
Pseudo R^2	0.29	0.30

Notes: *significant at 10%, ** significant at 5%; *** significant at 1%. d stands for dummy variable.
¤ Marginal effects are estimated at the sample mean except for the dummy variables.

In contrast to what was expected, being a second-generation producer, the size of the enterprise, and the wealth of a producer do not explain being ethnically tied.

5.4.2 Effect of Ethnic Ties on Performance of Producers

Propensity Score Matching

Using the same explanatory variables as in the probit regression, a propensity score matching is done between ethnically tied and non-ethnically tied producers using kernel matching[27] in order to check whether ethnic ties have a positive or negative impact on performance of producers. The results of the match are presented in Table 5.3 both for the whole sample and immigrant producers only.

The figures presented in Table 5.3 are based on the matching results made on the logarithm of profit, but are converted back into levels in order to make the results easier to interpret. Logarithm of profit is used in PSM in order to be consistent with the OLS regression. The reasons for the use of the log linear specification in the OLS regression are given in footnote 30.

The matching is done between producers from the treated (ethnically tied) and non-treated (non-ethnically tied) groups that are on the Common Support. As shown in Table 5.3, ethnically tied producers have a monthly average profit of 50.31 birr (5.24 US$)[28] less than that of matched producers that are not ethnically tied. The loss in profit is even higher for immigrant producers, where the average monthly profit for ethnically tied producers is 82.01 birr (8.54 US$) less than that of the matched counterparts. This is equivalent to a 24.3 pecent[29] and 29.1 percent decrease in average monthly profit due to ethnic ties for all producers and immigrant producers respectively. This finding shows that the negative effects of ethnic ties have offset the positive effects.

[27] STATA software on PSMATCH2 developed by Edwin Leuven and Barbra Sianesi is used.
[28] The 2008 exchange rate was 9.6 birr : 1 US$
[29] The percentage increase in monthly average profit is calculated as the difference in average profit between matched ethnically tied and non-ethnically tied producers divided by the average profit of matched non-ethnically tied producers.

Table 5.3 Average monthly profit in birr for ethnically tied and non-ethnically tied producers¤.

	Ethnically tied producers (Treated)	Non-ethnically tied producers (Non-treated)	Difference
Whole Sample			
Unmatched	156.65	343.44	-186.79
Matched (ATT)	156.34	206.65	-50.31 (0.15)**
Immigrants Only			
Unmatched	185.30	359.60	-174.29
Matched (ATT)	199.74	281.74	-82.01 (0.21)*

Notes: *significant at 10%, ** significant at 5%; *** significant at 1%.
¤The standard error for the Average Treatment Effect of the Treated (ATT) are in parentheses and is estimated after bootstrapping 100 times.

To check how the matching has performed in terms of eliminating differences in observable explanatory variables between the matched ethnically tied and non-ethnically tied producers, balancing tests are performed. Following Sianesi (2004) and Smith and Todd (2005), we use a chi square test for the joint significance of variables used in the probit model before and after the match. The chi square test after the match confirms that all the variables in the probit model are not jointly significant with prob>$\chi 2$ = 0.45 and prob>$\chi 2$= 0.99 for the whole sample and immigrant producers respectively (Table 5.I.2 in Appendix 5.I). This implies that there is no systematic difference in the distribution of observable covariates included in the PSM between the matched ethnically tied and non-ethnically tied producers. This shows that the matching procedure has performed well.

OLS regression

Tables 5.4 and 5.5 show the results of the OLS regression using the logarithm of monthly profit[30] as dependent variable and the ethnic tie dummy and other controls used in the PSM

[30] A log linear specification is chosen because the skewness/kurtosis normality test shows that the residuals of the OLS regression using the level-dependent variable, monthly profit, are not normally distributed while the residuals from the logarithm of monthly profit are normally distributed.

as explanatory variables both for the whole sample and immigrant producers[31]. In using logarithm of profit, we lose six observations that had negative profits. In addition to using a dummy for ethnic ties in the regression, we also use a continuous variable that measures the proportion of traders that are of the same ethnic group as a producer as defined in section 5.2.2. The estimation is done both on the unmatched sample and the matched sample from the PSM.

For producers in the whole sample, (ceteris paribus), being ethnically tied measured using the dummy, reduces profit significantly by about 20.0 and 29.0 percent for the unmatched and matched samples respectively (Table 5.4). The percentage reduction in profitability due to ethnic ties found using the OLS estimation on the matched sample (29.0 percent) is higher than the percentage reduction of 24.3 percent found in the PSM. For producers in the whole sample, (ceteris paribus), ethnic ties measured using the continuous variable, reduces profit significantly by 22.0 and 25.0 percent for the unmatched and matched samples respectively (Table 5.4). The result for the matched sample (25.0 percent) is close to what we find in the PSM (24.3 percent).

For immigrant producers there is no significant result for both measures of ethnic ties for the unmatched sample (Table 5.5). For the matched sample, however, a significant result is found with a reduction in profitability of 27.0 percent using both the dummy and continuous measures of ethnic ties. The reason why no significant results were found for the unmatched sample could be due to outliers that may have increased the variance, preventing more efficient estimates in OLS.

In all models for the whole sample (Table 5.4), more units of labor and machinery, owning a workshop and having more years of experience increase profit significantly. Producers belonging to the majority ethnic group (*Gamo*) and those selling their output in open markets have a significantly lower profit. For the unmatched producers of the whole

[31] A chow test between the whole sample and the subsample for immigrants shows a significant difference in coefficients across the two, justifying the need to have two separate OLS regressions.

sample, a significantly higher profit is found for immigrant producers, producers that are members of producers' cooperatives and producers with more years of schooling.

Table 5.4 OLS regression for the whole sample (dependent variable: log monthly profit) ¤

	Unmatched sample		Matched sample	
Ethnic ties[d]	-0.20 (0.10)*	-	-0.29 (0.14)*	-
Ethnic ties[c]	-	-0.22 (0.11)**	-	-0.25 (0.15)*
Male[d]	0.09 (0.38)	0.09 (0.38)	0.19 (0.16)	0.18 (0.16)
Age	-0.02 (0.02)	-0.02 (0.02)	-0.05 (0.03)	-0.05 (0.03)
Age squared	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Schooling	0.03 (0.01)**	0.03 (0.01)**	0.02 (0.02)	0.02 (0.02)
Experience	0.01 (0.01)**	0.01 (0.01)**	0.02 (0.01)***	0.02 (0.01)***
Second generation[d]	0.07 (0.10)	0.07 (0.10)	0.07 (0.15)	0.06 (0.15)
Immigrant[d]	0.21 (0.10)**	0.21 (0.10)**	0.15 (0.13)	0.14 (0.14)
Ethnic majority[d]	-0.44 (0.12)***	-0.44 (0.12)***	-0.36 (0.19)*	-0.36 (0.20)*
Member of producers' cooperative[d]	0.23 (0.13)*	0.22 (0.13)*	0.04 (0.17)	0.02 (0.17)
Starting capital borrowed from relatives (%)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Open market[d]	-0.65 (0.13)***	-0.64 (0.12)***	-0.58 (0.15)***	-0.56 (0.15)***
Contract[d]	0.15 (0.17)	0.15 (0.17)	0.33 (0.24)	0.35 (0.24)
Number of persons working in the enterprise	0.15 (0.05)***	0.15 (0.05)***	0.17 (0.06)***	0.17 (0.06)***
Current value of machinery & equipment	0.01 (0.01)*	0.01 (0.01)**	0.02 (0.01)**	0.02 (0.01)**
Ownership of workshop[d]	1.53 (0.50)***	1.54 (0.49)***	1.08 (0.54)**	1.06 (0.55)**
Access to electricity[d]	0.05 (0.12)	0.04 (0.12)	0.16 (0.18)	0.15 (0.18)
Constant	6.01 (0.56)***	6.04 (0.57)***	6.57 (0.65)***	6.62 (0.64)***
R^2	0.33	0.33	0.29	0.28
Number of observations	467	467	463	463

Notes: *significant at 10%, ** significant at 5%; *** significant at 1%. d stands for dummy variable and c stands for continuous variable. ¤ robust standard errors corrected for any form of arbitrary heteroskedasticity are reported in parenthesis.

Table 5.5 OLS regression for immigrant producers (dependent variable: log monthly profit) ¤

	Unmatched sample		Matched sample	
Ethnic ties[d]	-0.16 (0.14)	-	-0.27 (0.15)*	-
Ethnic ties[c]	-	-0.19 (0.13)	-	-0.27 (0.15)
Male[d]	0.75 (0.72)	0.75 (0.73)	0.47 (0.83)	0.47 (0.83)
Age	-0.04 (0.03)	-0.04 (0.03)	-0.07 (0.03)**	-0.07 (0.03)**
Age squared	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)*	0.00 (0.00)*
Schooling	-0.00 (0.02)	-0.00 (0.02)	-0.00 (0.03)	-0.00 (0.03)
Second generation[d]	0.21 (0.15)	0.21 (0.15)	0.10 (0.17)	0.10 (0.17)
Year since immigrated	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)
Ethnic majority[d]	-0.44 (0.18)**	-0.45 (0.18)**	-0.56 (0.22)**	-0.57 (0.22)**
Member of producers' cooperative[d]	0.41 (0.19)**	0.40 (0.18)**	0.46 (0.23)**	0.44 (0.23)**
Starting capital borrowed from relatives (%)	-0.00 (0.00)*	-0.00 (0.00)*	-0.00 (0.00)	-0.00 (0.00)
Open market[d]	-0.80 (0.17)***	-0.80 (0.16)***	-0.78 (0.19)***	-0.77 (0.19)***
Contract[d]	0.21 (0.23)	0.21 (0.22)	-0.00 (0.29)	0.01 (0.28)
Number of persons working in the enterprise	0.25 (0.06)***	0.24 (0.06)***	0.22 (0.07)***	0.22 (0.07)***
Current value of machinery & equipment	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
Constant	6.01 (0.56)***	6.05 (0.94)**	7.25 (1.05)***	7.33 (1.06)**
R^2	0.37	0.37	0.31	0.30
Number of observations	215	215	204	204

Notes: *significant at 10%, ** significant at 5%; *** significant at 1%. d stands for dummy variable and c stands for continuous variable. ¤ robust standard errors corrected for any form of arbitrary heteroskedasticity are reported in parenthesis.

In all models for immigrant producers only (Table 5.5), more units of labor have a significant positive effect on profit. Compared to the models of the whole sample, machinery and equipment are not any more significant. Similar to the whole sample, producers that are members of the majority ethnic group (*Gamo*) and producers that sell their output in open markets have a significantly lower profit. On the other hand, producers that are members of producers' cooperatives have significantly higher profits (Table 5.5).

5.5 Conclusions and Discussion

This paper analyzes various socio-economic factors leading to ethnic ties in trade relationships and investigates the effect on economic performance by taking small-scale producers of the handloom sector in Ethiopia as a case study and using a parametric and a non-parametric statistical method.

Recent immigrants and less experienced producers are more likely to be ethnically tied. This may be caused by the lack of time and resources at hand to establish a wide network of business-related contacts with traders. Ethnic ties are also found to be important for producers operating in remote areas. Ethnic ties in remote areas may help to reduce risks associated with marketing and facilitate trust in long-distance trades. On the other hand, producers with a wide network of business-related contacts with different traders such as those operating in producers' cooperatives are less likely to be ethnically tied. Ethnic ties in credit provision are also found to lock producers into trade relationships by increasing the cost of credit and decreasing the probability of trading with 'outsiders' (Portes, 1995a).

Although ethnic ties can positively impact business outcomes by reducing transaction costs and facilitating access to various resources, the non-parametric estimate of the PSM reveals that ethnic ties result in lower profit. This could be due to forgone economies of scale from having limited flows of new business-related ideas in closed social networks that can offset the benefits of ethnic ties. An exclusive social network can also restrict the extent of business relationships to a limited number of agents who can change the power structure and manipulate the exchange process depending on their control over 'power resources' such as information about prices, markets, capital and credit (Nadvi, 1999; Lyon, 2000; Alesina and La Ferrara, 2005). The loss in profit due to ethnic ties is found to be even higher for immigrant producers. This is probably due to the tendency to have more 'immigrant-solidarity' that arises from a common cultural background, which often results in a greater density of social networks, thereby lowering the probability of assimilating with 'outsiders' (Portes, 1995b). After controlling for the same observable covariates as in the non-parametric matching method, the OLS regressions further confirm that both the binary and continuous measures of ethnic ties result in lower profits.

In general, producers will continue to transact with traders from the same ethnic group, even with low returns, as long as the losses incurred by having closed social networks are offset by the problem-solving capacity of ethnic ties when there are market imperfections (Bowles and Gintis, 2004). The losses in profit from ethnic ties can be considered as a shadow price of transacting with 'outsiders', which might indicate the cost of intervention needed in order to reduce the various market imperfections faced by producers. Such an intervention can be made for example by providing access to business development services such as training, marketing assistance, information, credit, business linkages and promotion that can be provided by individuals, private for-profit firms, non-government organizations, and government agencies.

The main limitation of this study is its inability to control for unobservable factors like the talent, beliefs and risk behavior of producers that can affect both the likelihood of being ethnically tied and their profitability. Despite this limitation the study adds to the growing literature that is exploring the role and impact of social networks on small-scale producers in developing countries.

Appendix 5.I

Table 5.I.1 Descriptive statistics of variables

Variables	Mean		Std.Dev		Min		Max	
	a	*b*	*a*	*b*	*a*	*b*	*a*	*b*
Male[d]	0.99	0.99	0.12	0.09	0	0	1	1
Age	36.74	38.24	13.58	13.91	15	16	75	75
Schooling	4.82	4.13	3.65	3.42	0	0	14	12
Experience	16.73	16.72	13.24	14.05	0	0	72	57
Second generation[d]	0.67	0.68	0.47	0.47	0	0	1	1
Immigrant[d]	0.46	--	0.49	--	0	--	1	--
Year since Immigrated	--	18.66	--	13.43	--	0	--	60
Ethnic majority[d]	0.79	0.74	0.41	0.44	0	0	1	1
Member of producers' cooperative[d]	0.19	0.27	0.39	0.44	0	0	1	1
Starting capital borrowed from relatives (%)	34.36	31.13	45.83	45.49	0	0	100	100
Open market[d]	0.84	0.75	0.37	0.44	0	0	1	1
Contract[d]	0.08	0.12	0.27	0.33	0	0	1	1
Number of persons working in the enterprise	1.62	1.59	1.10	1.26	1	1	8	8
Current value of machinery & equipment(birr)	326.49	447.84	777.34	1029.55	6	15	7120	7120
Ownership of workshop[d]	0.01	0.009	0.12	0.09	0	0	1	1
Access to electricity[d]	0.70	0.90	0.46	0.30	0	0	1	1
Monthly profit (birr)	374.73	435.90	799.72	517.57	-816.67	0	14330.83	3041.67

Notes: Figures in columns '*a*' are for the whole sample and figures in columns 'b' are for immigrants. d stands for dummy variable.

Table 5.I.2 Chi square test for the joint significance of variables

	Pseudo R^2	LR chi^2	p>chi^2
Whole Sample			
Unmatched	0.31	183.04	0.00
Matched	0.02	16.07	0.45
Immigrants Only			
Unmatched	0.22	65.95	0.00
Matched	0.01	3.76	0.99

CHAPTER 6

Conclusions and Discussion

6.1 Summary of Main Findings

This study empirically investigates how clustering and social networks affect the performance of MSEs in Africa by looking at the evidence from the handloom sector in Ethiopia. Using more than 4000 micro enterprises from the 2002/03 survey on Cottage/Handicraft Manufacturing Industry conducted by the Central Statistical Agency of Ethiopia, Chapter 2 presents a detailed counterfactual investigation where the performance of micro enterprises, in terms of profit, is compared with that of dispersed ones in four regions of Ethiopia both in urban and rural areas. To take into account for the problem of selection bias that may arise from entrepreneurs decision to locate their business in a certain location, clustered micro enterprises are matched with dispersed ones that have the same observable characteristics except for being clustered using the non-parametrical statistical method of propensity score matching (PSM)[32]. These characteristics are classified into enterprise and regional specific factors where it is further investigated how they determine the clustering of micro enterprises in rural and urban areas.

[32] PSM only eliminates biases that arise from observables. Hence, we cannot completely rule out the possibility that clustered and dispersed enterprises might still differ based on some unobservable characteristics.

Enterprise and regional specific factors are found to determine clustering of micro enterprises in rural and urban areas differently. While micro enterprises that are run by female and younger operators are more likely to cluster in rural areas, this is not the case in urban areas. Loening et al., (2008) also found that young females are the main operators of non-farm enterprises in rural Ethiopia, highlighting the existence of more female operators in rural than urban areas. On the other hand, enterprises that are run by more educated entrepreneurs are more likely to cluster both in rural and urban areas. This result is in accordance with Freedman, (2008) and Combes et al., (2008) who noted that industrial clusters tend to attract more educated workers or operators with better skills because they are capable of "capitalizing on agglomeration benefits" through their superior information processing ability and search techniques compared to less educated workers. Besides, the high mobility and entrepreneurial tendencies of young and educated adults could also attract them to areas with better access to markets and information (Wheeler, 2006).

Micro enterprises are more likely to cluster around big textile factories both in urban and rural areas. Similar with this finding, Fujita and Thisse (1996) and Lall et al., (2003) illustrated that producers benefit from the existence of big firms from the same industry due to various inter-industry externalities. With regard to banking services, micro enterprises in urban areas are found to cluster further away from Micro Finance Institutes (MFIs), while no significant effect is found for rural areas. The importance of informal finances like borrowing from friends and families and trade credits within clusters (Steel et al., 1997; Buckley, 1997), could have substituted the role of MFI services in urban areas by easing the constraint on working capital. Ruan and Zhang (2009) also showed that industrial clusters, through intensive division of labor, can help micro enterprises overcome financial constraints by allowing them specialize according to their capital portfolio.

Micro enterprises in urban areas are more likely to cluster around markets and closer to an all-weather road while micro enterprises in rural areas cluster in remote areas further away from markets. The latter could indicate that there is more need to cluster in rural areas to compensate for remoteness. This is in line with the finding by Weijland (1999) who noted that industrial clusters in remote areas are important to attract traders that help to link cottage industries with distant markets. Traders are usually attracted to such clusters because the “trading cost per transaction” is lower when producers are concentrated in one area (ibid). Micro enterprises in general are more likely to cluster in the capital city Addis Ababa than in other urban areas and cluster more in rural towns.

The results of the matching procedure confirms that clustering results in higher profit compared to dispersed locations after controlling for selection bias. The increase in profit is found to be higher in urban than rural areas, which implies that urban cluster provide more location economies than rural clusters possibly due to increased cooperation and joint action among producers in order to meet the requirements of large markets in urban areas.

Chapter 3 further investigates the advantages of clustering by emphasizing on the role of easing the financial constraints of micro enterprises in the absence of a well-functioning capital market. Using the same data set as in Chapter 2, the effect of clustering on starting capital of micro enterprises is investigated after controlling for capital market inefficiency, among other factors. Clustering is found to ease the financial constraints of micro enterprises by lowering the capital entry barrier through the reduction of the initial investment required to start a business. This effect is found to be significantly larger for enterprises investing in districts of high capital market inefficiency. The results are also found to be robust for different measures of clustering. This finding is in line with a number of studies conducted in China, where clustering through specialization and division of labor is found to enable large number of small entrepreneurs to enter the industry by helping them overcome the financial constraints in the early stage of industrialization (Huang et al., 2008; Ruan and Zhang, 2009; Long and Zhang, 2011).

Using more than 2000 rural households from the 2006/07 Rural Investment Climate Survey conducted by the World Bank and the CSAE, Chapter 4 investigates how clustering affects a farm household’s decision to enter into and exit from non-farm enterprises. After controlling for household characteristics, various indicators of the investment climate and exogenous shocks of rainfall variability, the existence of clusters of micro enterprises operating in the same district increases the likelihood of farm households to start a non-farm enterprise. With a similar positive effect but of less magnitude, the concentration of big manufacturing activities is also found to increase the likelihood of farm households to start a non-farm enterprise. Non-farm enterprises operating in clusters are found to be less likely to exit their business than those operating outside of clusters. Rural towns are also found to promote entry into non-farm enterprises and lower their exit. Similarly, access to an all-weather road is found to increase the likelihood of entry into non-farm enterprises. The impact of entry and exit into and from non-farm enterprises on household's well-being is further investigated by using total household income, the food security status of a household and its ability to raise enough money in case of an emergency, as indicators. Using propensity score matching to account for selection bias on observables, it is found that, entry into non-farm enterprises significantly increases household income and boosts their food security status. Exit from non-farm enterprises, on the other hand, is found to significantly reduce households' income.

Chapter 5 investigates various socio-economic factors leading to ethnic ties in trade relationships and examines the effect on economic performance by taking small-scale producers of the handloom sector in Ethiopia as a case study. To look at the impact of ethnic ties on performance, the chapter uses both the (parametric) OLS regression and the non-parametric statistical method of propensity score matching and the results are compared accordingly. The data used in this chapter is a cross section survey on 486 producers in nine different clusters of rural and urban areas, collected by IFPRI and EDRI in 2008.

Recent immigrants and less experienced producers that may lack the time and resource to establish a wide network of business-related contacts with traders, are found to have a higher likelihood of being ethnically tied. A similar finding was seen in the surgical instrument cluster in Pakistan, where ethnic ties and family relationships are important for providing information and a material basis at the start of the business (Nadiv, 1999). Ethnic ties are also found to be important for producers operating in remote areas as a means to reduce risks associated with marketing and facilitate trust in long-distance trades. On the other hand, producers with a wide network of business-related contacts with different traders such as those operating in producers' cooperatives are less likely to be ethnically tied. Ethnic ties in credit provision are also found to lock producers into trade relationships. Fafchamps (2000) and Fisman (2001) noted that ethnicity and family linkages are often used by traders in developing countries to screen potential business partners and provide capital to producers, especially in the initial phase of their business.

Although ethnic ties can positively impact business outcomes by reducing transaction costs and facilitate access to various resources, the non-parametric estimate of the propensity score matching reveals that ethnic ties result in lower profit. A similar negative effect on performance of small firms in India and Pakistan is also found by Annen (2001), where exclusive social networks based on common identity result in forgone economies of scale due to limited flow of new business related ideas. The loss in profit due to ethnic ties is found to be even higher for immigrant producers. Portes (1995b) noted that immigrants tend to have more solidarity due to their common cultural background, which often results in a greater density of social networks, thereby lowering the probability of assimilating with 'outsiders'. After controlling for the same observable covariates as in the non-parametric matching method, the OLS regressions further confirm that ethnic ties result in lower profits.

6.2 Discussion and Policy Implications

Naturally emerged clusters of MSEs are predominantly common in Ethiopia in traditional and labor intensive sectors in rural and poor urban areas. This has attracted the interest of policy makers and development agencies like World Bank, UNIDO and ILO to promote such clusters because of the direct impact they have on poverty. A cluster based development for MSEs has also been given a top priority in the country's current 5 years

Growth and Transformation Plan (GTP). Owing to the existing policy enthusiasm, the findings of this study will provide an additional perspective to assist the ongoing efforts by the government and different agencies and highlight potential avenues for intervention and investment targeting.

Rural Towns and Cluster Formation

Findings of this study disclose that large cities and rural towns increase the probability of clustering. Rural towns are also found to promote entry and enhance the survival of rural firms. This points to the importance of urbanization economies on top of location economies to improve the performance of MSEs and enhance market integration. Even if there may not be any direct contractual relationships or buyer-supplier linkages between large firms and MSEs operating in bigger towns, MSEs can still benefit from other forms of externalities such as information and technological spillovers, availability of a pool of skilled workers, and existence of common services such as research and training centers, government and regulatory institutions, etc. In a study compiled by the World Bank on 11 different MSEs clusters in Africa, proximity to major local markets and roads are also found to play an important role for clusters to emerge (Zeng, 2008). Assisting rural towns by providing basic infrastructure like road and electricity access, supporting institutions and building a conducive business environment could therefore be one way to help facilitating the formation and growth of MSEs clusters. In their comparison between rural and urban manufacturing enterprises in Ethiopia, Rijkers et al., (2010) suggested that promoting rural towns could play an important role to have a more geographically focused intervention to improve the performance of rural firms. The development of rural towns could also have a trickle-down effect to surrounding and remote rural areas by increasing the demands for local agricultural products (Haggblade et al., 2007).

The findings of this study also indicate that regional specific factors that determine clustering of micro enterprises differ between rural and urban areas. This highlights the need to focus on the existing local circumstances when formulating policies that can promote clustering. Apart from location specific factors, the benefits of clustering and hence factors that attract entrepreneurs towards clusters could be sector specific (Weijland, 1999). Policies should therefore be revisited and adapted to changing circumstances and the competitive positions of specific sectors located in specific locations.

Clustering and Capital Market Imperfections

Lack of access to finance remains to be a major obstacle to the expansion and growth of MSEs in Africa (Demirgüç-Kunt and Maksimovic 1998; Rajan and Zingales 1998; Ayyagari et al., 2008). Even if financial development is crucial for industrial development, developing a well-functioning capital market is a daunting task in many developing countries. Under such circumstances, it is important to look for alternative approaches to propagate industrialization when local conditions do not allow easy access to credit. The findings in Chapter 3 indicate that industrial clusters could be one way to promote industrialization even in the absence of a well-functioning capital market. The findings are not suggesting that industrial clusters could make the capital market work efficiently, rather industrial clusters could serve as a get way to promote entrepreneurship and help MSEs circumvent the constraints they face. Through a reduced capital entry barrier, industrial clusters can also allow entrepreneurs with limited capital to engage in productive activities and hence add to the overall household income (Zhang, 2011). Promoting industrial clusters, especially in divisible sectors could therefore help "tap the entrepreneurial talents" and make "better use of limited capital" in MSEs (Ruan and Zhang, 2008).

Innovation and Cluster Growth

Taken together, the findings in Chapter 2, 3 and 4 indicate that clustering makes MSEs more profitable, eases entry barriers and enhances their survival. However, these findings are based on cross-sectional data and hence there should be caution when formulating policies that promote clustering in the long run. This is because, although location economies within clusters could make MSEs more profitable, the increased clustering, following ease of entry, could result in the expansion of the supply of products, which in turn can have a downward pressure on price and profit margins. The continued entry of enterprises could also result in congestion having an upward pressure on rental prices and reducing operational efficiency (Sonobe and Otsuka, 2006a).

Several case studies of MSEs cluster in East Asia and Latin America have demonstrated the importance of innovation, which is manifested by differentiated products through improved product quality and altered marketing channels as a way to maintain profitability and foster sustained growth within clusters (Altenburg and Mayer-Stamer, 1999; Sonobe and Otsuka, 2006a). However, most MSEs cluster in Africa are categorized as "survival" where the business culture is dominated by imitation, often lacking the capacity both in terms of the appropriate skill and capital to invest and innovate (Banji and McCormick, 2007; Zeng, 2008; Yoshino, 2011). From a policy perspective, it is therefore important to understand how to create an environment that stimulates innovation and constant upgrading in order to have a continued growth of clusters that have already emerged.

However, upgrading efforts should also take into account the possible heterogeneity in firm's performance, innovative capabilities and production history. Applying a uniform polices of MSEs cluster development might be a wrong approach as enterprises are diverse in their potentials. A recently conducted need-based intervention in two MSEs clusters in Nairobi, Kenya and Kumasi, Ghana by the Foundation for Advanced Studies in International Development (FASID) from 2007-2009 could be good examples (cited in Yoshino, 2011). After identifying lack of entrepreneurial skills and knowledge as the major constraints from survey responses of clustered producers, a series of scientifically designed field experiments were conducted that provided a managerial training programme. It was found that entrepreneurs who received formal managerial training achieved better business results in terms of larger growth in sales and gross profit than those who had not received any formal training. The managerial training program is also found to be correlated with improved physical efficiency in production.

Social Networks and Market Imperfections

Chapter 5 gives another perspective of how market integration can be enhanced despite the absence of physical proximity. The findings indicate that ethnic ties continue to play an important role in MSE's trade relationships especially for less experienced producers and new beginners, even with low returns, as long as the losses incurred by having closed social networks are offset by the problem-solving capacity of ethnic ties when there are market imperfections. The losses in profit from ethnic ties can be considered as a shadow price of transacting with 'outsiders', which might indicate the cost of intervention needed in order to reduce the various market imperfections faced by producers. Such an intervention can be made for example by providing access to business development services such as training, marketing assistance, information, credit, business linkages and promotion. Such services can be provided by individuals, private for-profit firms, non-government organizations, and government agencies. By opening the possibility to transact and communicate with "outsiders", such kind of interventions will help producers acquire necessary technical and business related know-how, which are necessary to remain competitive.

Final Remarks

A caveat of this study is its reliance on cross-sectional data that makes it impossible to look at the dynamic aspects of cluster development and performance. Limited data availability has also contained the study from investigating the impact of relative output and input prices in clustered and dispersed locations on performance. In addition, the lack of cross-sectoral and cross-country analysis due to limited data availability restricts drawing more generalized conclusions about the prospects and challenges of MSEs clusters in Africa. The fact that there was no spatial data available has also limited the study to use political boundaries in order to define industrial clusters. This has restricted the study from capturing the actual effect of neighbourhood dynamics and spill-overs on entrepreneurs location decisions and hence the impact on their performance. Moreover, lack of valid instrumental variable to capture the endogeniety that may arise from clustering has restricted the study from inferring causal linkages between clustering and MSEs performance. Despite these limitations, the study provides a flexible way to better understand the advantages of clustering through a detailed counter factual investigation that accounts for selection bias arising from observable factors. More generally, this study helps narrow the gap in the literature on cluster based development in primarily agricultural economies in Africa that are at an early stage of industrialization, and currently with low levels of non-farm activi

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SUMMARY

The private sector is often listed as a key driving force for industrialization in Africa in the development literature. A critically important role is played by micro- and small-scale enterprises (MSEs), which constitute the lion's share of the private sector in Africa. MSEs account for more than 90% of all firms outside of the agricultural sector and 50-60% of the off-farm employment in Africa. With this regard, promoting entrepreneurship in MSEs and stimulating their growth is viewed as a key instrument in poverty reduction efforts both by development agencies and policymakers.

Despite their large employment contribution, MSEs are characterized by low productivity and constitute an insignificant share of the commercial output in most African economies. Lack of market integration is often mentioned as one of the reasons as to why the performance of MSEs has remained poor in many African countries. Lack of market integration due to low firm density and long distances to markets results in loss of external economies of scale and high transaction costs, which could undermine MSEs' capacity to take advantage of trade and investment opportunities. The major challenge for MSEs is therefore, to increase their performance by means of improved market integration.

In recent literatures, industrial clusters (the geographic concentration of economic activities) and social networks are noted as having the potential to enhance market integration and reduce the transaction costs of doing business among firms. Although considerable attention has been given in the literature to the advantages of industrial clusters for business activities, much of previous researches have evolved around large-scale enterprises operating in large metropolitan regions where markets are relatively well integrated, competitive and technologically advanced. The potential advantages of industrial clusters for MSEs that operate in fragmented and uncompetitive markets such as in Africa is little studied. The few studies available in Africa also focus on case studies, often lacking a comparative analysis. Moreover, an empirical investigation on the role and

impact of social networks on MSEs in Africa was long constrained by the lack of adequate data on detailed social relationships among different agents.

The general objective of this study is to empirically investigate how clustering and social networks affect the performance of MSEs in Africa by looking at the evidence from the handloom sector in Ethiopia. Ethiopia provides a relevant context to address this objective due to the co-existence of clustered and non-clustered or dispersed MSEs both in urban and rural areas. Besides, the availability of large scale cross-sectional surveys on MSEs allow us to implement a detailed counter factual investigation between clustered and dispersed MSEs and look at the impact of clustering and social-networks on their performance. From this general objective, the following four specific objectives are defined and analysed in separate chapters. 1). To investigate clustering advantages by contrasting the performance of clustered micro enterprises, in terms of profit, with that of control groups of dispersed ones both in urban and rural areas. The study also aims to identify factors determining clustering of micro enterprises in urban and rural areas. 2) To examine the advantage of clustering in easing the financial constraints of microenterprises. 3) To investigate how clustering affects the entry and exit decisions of farm households into and from non-farm enterprises in rural parts of Ethiopia and examine the impact of entry into and exit from non-farm enterprises on household's wellbeing, and 4) To identify various socio-economic factors that determine ethnic ties between producers and traders and analyse how these ethnic ties affect the performance of producers.

Using more than 4000 micro enterprises from the 2002/03 survey on Cottage/Handicraft Manufacturing Industry conducted by the Central Statistical Agency of Ethiopia (CSAE), Chapter 2 addresses the first objective of the study and presents a detailed counterfactual investigation where the performance of micro enterprises, in terms of profit, is compared with that of dispersed ones in four regions of Ethiopia both in urban and rural areas. To take into account for the problem of selection bias that may arise from entrepreneurs decision to locate their business in a certain location, clustered micro enterprises are matched with dispersed ones that have the same observable characteristics except for being clustered using the non-parametrical statistical method of propensity score matching. In addition, this chapter examines various enterprise and regional specific factors that determine the clustering of micro enterprises in rural and urban areas. Clustering is found to result in higher profit compared to dispersed locations. The increase in profit from clustering is found to be higher in urban than rural areas. It is also found that regional specific factors determining clustering of micro enterprises are different in urban and rural areas.

In addressing the second objective, Chapter 3 further investigates the advantage of clustering by emphasizing on the role to ease the financial constraints of micro enterprises in the absence of a well-functioning capital market. Using the same data set as in Chapter 2, the effect of clustering on starting capital of micro enterprises is investigated after controlling for capital market inefficiency, among other factors. Clustering is found to ease the financial constraints of micro enterprises by lowering the capital entry barrier through the reduction of the initial investment required to start a business. This effect is found to be significantly larger for enterprises investing in districts with a high level of capital market inefficiency.

Using more than 2000 rural households from the 2006/07 Rural Investment Climate Survey conducted by the World Bank and the CSAE, Chapter 4 investigates how clustering affects farm household's decision to enter into and exit from non-farm enterprises. After controlling for household characteristics, various indicators of the investment climate and exogenous shocks of rainfall variability, it is found that the existence of clusters of micro enterprises operating in the same district increases the likelihood of farm households to start a non-farm enterprise. Non-farm enterprises operating in clusters are also found to be less likely to exit their business than those operating outside of clusters. The study further investigates the impact of entry and exit into and from non-farm enterprises on farm household's well-being by using total household income, the food security status of a household and the household's ability to raise enough money in case of emergency, as indicators. Using propensity score matching to account for selection bias, it is found that, entry into non-farm enterprises significantly increases household's income and food security status. Exit from non-farm enterprises, on the other hand, is found to significantly reduce household's income.

Chapter 5 addressed the last objective of the study and investigates various socio-economic factors leading to ethnic ties in trade relationships and examines the effect on economic performance by taking small-scale producers of the handloom sector in Ethiopia as a case study. To look at the impact of ethnic ties on performance, the chapter uses both (parametric) OLS regression and the non-parametric statistical method of propensity score matching and the results are compared accordingly. The data used in this chapter is a cross section survey on 486 producers in nine different clusters of rural and urban areas, collected by IFPRI and EDRI in 2008. Results show that ethnic ties play an important role for recent immigrants and less experienced producers and for those operating in remote areas further away from market. Ethnic ties in credit provision are also found to lock producers into trade relationships. The impact of ethnic ties on the economic performance of producers further reveals that ethnic ties result in lower profits. And the loss in profit due to ethnic ties is found to be higher for immigrant producers. The results are robust for both parametric and non-parametric statistical methods.

The last chapter of this thesis (Chapter 6) provides the main conclusions and a discussion of the research and provide potential avenues for intervention and investment targeting to help promote clusters and enhance the performance of MSEs.

SAMENVATTING (SUMMARY IN DUTCH)

In de ontwikkelingsliteratuur wordt de private sector vaak gezien als een belangrijke stimulerende kracht voor industrialisatie in Afrika. Een beslissende rol wordt gespeeld door micro- en kleinschalige ondernemingen (MSE's) die het leeuwendeel van de Afrikaanse private sector vormen. Meer dan 90% van alle bedrijven buiten de agrarische sector zijn MSE's en zij zijn goed voor 50-60% van de werkgelegenheid buiten de landbouw in Afrika. Dat is de reden dat ontwikkelingsorganisaties en beleidsmakers het ondernemerschap in MSE's willen bevorderen en het stimuleren van de groei van MSE's beschouwen als belangrijk instrumenten om armoede te verminderen.

Ondanks hun grote bijdrage aan de werkgelegenheid worden MSE's gekarakteriseerd door lage productiviteit en leveren ze een onbelangrijk deel van de commerciële output in de meeste Afrikaanse economieën. Een gebrek aan marktintegratie wordt vaak genoemd als een van de redenen voor het slechte presteren van de MSE's in veel Afrikaanse landen. Gebrek aan marktintegratie als gevolg van een lage concentratie van bedrijven en lange afstanden naar de markt resulteert in verlies van extern schaalvoordeel en hoge transactiekosten, wat de capaciteit van de MSE's om te profiteren van handel en investeringmogelijkheden zou kunnen ondermijnen. De grootste uitdaging voor MSE's is daarom om hun prestatie te verbeteren door middel van een verbeterde marktintegratie.

In recente literatuur worden industriële clusters (de geografische concentratie van economische activiteiten) en sociale netwerken erkend als potentiële bevorderaars van marktintegratie, verder kunnen ze transactiekosten van zakelijke activiteiten tussen bedrijven verminderen. Hoewel er in de literatuur aanzienlijke aandacht is besteed aan de voordelen van industriële clusters voor zakelijke activiteiten, heeft veel onderzoek zich gericht op grootschalige bedrijven opererend in grootstedelijke regio's, waar de markten relatief goed zijn geïntegreerd, competitief zijn en technologisch goed zijn ontwikkeld. De potentiële voordelen van industriële clusters voor MSE's die opereren in gefragmenteerde en niet-concurrerende markten zoals in Afrika zijn niet veel onderzocht. De weinige studies

beschikbaar over Afrika zijn ook gericht op casestudies; vaak ontbreekt een vergelijkende analyse. Verder werd empirisch onderzoek naar de rol en effect van sociale netwerken op MSE's in Afrika lang beperkt door een gebrek aan goede data van gedetailleerde sociale verbanden tussen de verschillende betrokkenen.

De algemene doelstelling van dit onderzoek is om empirisch te onderzoeken hoe clustering en sociale netwerken van invloed zijn op de prestatie van MSE's in Afrika door te kijken naar het bewijs vanuit de weefsector in Ethiopië. Ethiopië verschaft hiervoor een relevante context, vanwege het bestaan van geclusterde en niet-geclusterde of verspreide MSE's in stedelijke en rurale gebieden. Daarnaast biedt de beschikbaarheid van grote cross-sectionele datasets over MSE's ons de mogelijkheid een gedetailleerd onderzoek uit te voeren naar geclusterde en verspreide MSE's en te kijken naar het effect van clustering en sociale netwerken op hun prestatie. Vanuit deze algemene doelstelling zijn de volgende vier specifieke doelstellingen gedefinieerd en geanalyseerd in verschillende hoofdstukken. 1) Het onderzoeken van clustervoordelen door de prestatie te vergelijken van geclusterde micro-ondernemingen, in termen van winst, met die van controlegroepen van verspreide bedrijven in stedelijke en rurale gebieden. Het onderzoek richt zich ook op het identificeren van factoren die clustering van micro-ondernemingen in stedelijke en rurale gebieden bepalen. 2) Het onderzoeken van voordelen van clustering als een manier om financiële beperkingen van micro-ondernemingen te versoepelen. 3) Het onderzoeken van hoe clustering de besluiten van boeren beïnvloedt om over te stappen op niet-agrarische ondernemingen en vice versa in rurale gebieden van Ethiopië en het effect daarvan te onderzoeken op het welzijn van de betreffende huishouding en 4) Het identificeren van verschillende sociaaleconomische factoren die de etnische banden bepalen tussen producenten en handelaren en te analyseren hoe deze etnische banden de prestatie van de producenten beïnvloeden.

Hoofdstuk 2 behandelt de eerste doelstelling van de studie en maakt daarbij gebruik van gegevens van meer dan 4000 micro-ondernemingen uit het 2002/2003 onderzoek "Cottage/Handicraft Manufacturing Industry" uitgevoerd door het Centraal Bureau van de

Statistiek van Ethiopië (CSAE). Het hoofdstuk beschrijft een gedetailleerd onderzoek waarin de prestatie van micro-ondernemingen, in termen van winst, wordt vergeleken met die van de verspreide ondernemingen in vier regio's van Ethiopië in stedelijke en rurale gebieden. Om rekening te houden met het probleem van selectiebias dat kan optreden door de beslissing van ondernemers om hun onderneming op een bepaalde locatie te situeren, worden geclusterde micro-ondernemingen vergeleken met verspreide bedrijven die dezelfde waarneembare kenmerken hebben met uitzondering van het geclusterd zijn, met gebruik van de non-parametrische statistische methode van propensity score matching. Dit hoofdstuk behandelt tevens verschillende ondernemings- en regionaal-specifieke factoren die de clustering van micro-ondernemingen in rurale en stedelijke gebieden bepalen. Er is gebleken dat clustering tot hogere winst leidt. De toename in winst is hoger in stedelijke dan in rurale gebieden. Er is ook gebleken dat regionaal-specifieke factoren die clustering van micro-ondernemingen bepalen, verschillen in stedelijke en rurale gebieden.

Hoofdstuk 3 behandelt de tweede doelstelling en onderzoekt verder het voordeel van clustering door de rol te onderzoeken die clustering heeft bij het versoepelen van financiële beperkingen van micro-ondernemingen bij afwezigheid van een goed functionerende kapitaalmarkt. Gebruikmakend van dezelfde data als in hoofdstuk 2 wordt het effect van clustering op het startkapitaal van micro-ondernemingen onderzocht na correctie voor o.a. de inefficiëntie van de kapitaalmarkt. Clustering bleek de financiële beperkingen van micro-ondernemingen te versoepelen door de toegang tot kapitaal te vergemakkelijken door middel van vermindering van de initiële investering, vereist om een onderneming te starten. Dit effect is significant groter voor ondernemingen die in districten investeerden met een sterk inefficiënte kapitaalmarkt.

Gebruikmakend van data van 2000 plattelandshuishoudens van de 2006/07 Rural Investment Climate Survey uitgevoerd door de Wereldbank en de CSAE wordt in hoofdstuk 4 onderzocht hoe clustering de beslissing beïnvloedt van boerenhuishoudingen om over te stappen op niet-boerenondernemingen en vice versa. Na correctie voor kenmerken van de huishouding, verschillende indicatoren van het investeringsklimaat en schommelingen in regenval, is gebleken dat het bestaan van clusters van micro-ondernemingen in hetzelfde district de waarschijnlijkheid verhoogt dat boerenhuishoudens overschakelen naar niet-boerenondernemingen. Tevens is gebleken dat het minder waarschijnlijk is dat niet-boeren ondernemingen opererend in clusters stoppen in vergelijking tot bedrijven die opereren buiten de clusters. De studie onderzoekt verder het effect van de overstap naar niet-boerenondernemingen op het welzijn van de boerenhuishouding gebruikmakend van de indicatoren het totale boereninkomen, de voedselzekerheid situatie van een huishouden en het vermogen om genoeg geld te genereren in het geval van nood. Met gebruik van propensity score matching om een eventuele selectiebias teniet te doen is gebleken dat het starten van een niet-boerenonderneming het inkomen en de voedselzekerheid significant verhoogt. Aan de andere kant bleek het stoppen met de niet-boerenonderneming het inkomen significant te verlagen.

Hoofdstuk 5 behandelt de laatste doelstelling van de studie en onderzoekt verschillende sociaaleconomische factoren die leiden tot etnische banden in handelsrelaties en onderzoekt het effect daarvan op economische prestatie. Hiervoor worden kleinschalige producenten in de weefindustrie in Ethiopië gebruikt als een case studie. Om het effect te bestuderen van de etnische banden op prestatie, worden in het hoofdstuk (parametrische) OLS regressie en de non-parametrische statistische methode van propensity score matching toegepast en worden de resultaten vergeleken. De gebruikte data in dit hoofdstuk komen uit een cross-sectionele studie van 486 producenten in negen verschillende clusters in rurale en stadsgebieden, verzameld in 2008 door IFPRI en EDRI. De resultaten laten zien dat etnische banden een belangrijke rol spelen bij recente migranten en minder-ervaren producenten en bij die bedrijven opererend in afgelegen gebieden verder bij de markt vandaan. Etnische banden in kredietverstrekking maken producenten afhankelijk van bepaalde handelsrelaties. Het effect van etnische banden op de economische prestatie van producenten resulteert in lagere winsten. Het laatste geldt vooral voor migrantenproducenten. De resultaten zijn robuust voor zowel de parametrische als non-parametrische statistische methoden.

Het laatste hoofdstuk van dit proefschrift (hoofdstuk 6) presenteert de belangrijkste conclusies en een discussie van het onderzoek en geeft mogelijke manieren voor interventie en doelen voor investeringen om clustervorming te stimuleren en de prestatie van MSE's te verbeteren.

Completed Training and Supervision Plan (TSP)

Name of Activity	Institute	Year	ECTS
1. Advanced Econometrics	WASS	2008	6
2. Economic Models	WASS	2008	6
3. Spatial Econometrics: theory and practice	WASS	2008	1.5
4. Theory and Practice of Efficiency and Productivity Measurement: Static Approaches	WASS	2008	1.5
5. Agri-food industrial organization	WASS	2008	1.5
6. Economic Theory II	NAKE	2008	3
7. Game Theory	NAKE	2009	6
9. Introduction course	WASS	2008	1.5
10. Techniques of Writing and Presenting a Scientific Paper	WASS	2008	1.2
11. Presentation at the CSAE conference on Economic Development in Africa.	Oxford University	2009	1
12. Presentation at the 7th International Conference on the Ethiopian Economy	Ethiopian Economic Association	2009	1
13. Presentation at the CSAE conference on Economic Development In Africa	Oxford University	2011	1
14. Presentation at EAAE Congress on Change and Uncertainty: Challenges for Agriculture, Food and Natural Resources	ETH Zurich, Switzerland	2011	1
15. Presentation at the international a conference on Increasing Agricultural Productivity and Enhancing Food Security: New Challenges and Opportunities	IFPRI	2011	1
		Total	33.2

CURRICULUM VITAE

Merima Abdella Ali was born in Addis Ababa, Ethiopia on May 21, 1981. She attended high school at Nazateth School in Addis Ababa. After finishing her high school, she joined Addis Ababa University in 2000 and studied her bachelors in Economics until 2004. After finishing her bachelors, she was employed at the Ethiopian Development Research Institute (EDRI) as a Junior researcher. In 2005, she went to Sweden to pursue her Masters in Economics at the University of Gothenburg, School of Business, Economics and Law. After finishing her Masters, she went back to EDRI and worked until 2007. In November 2007, she got an opportunity to do her PhD at the Agricultural Economic and Rural Policy Group of Wageningen University. During her PhD, she took various courses given both by the Wageningen School of Social Science and the Netherlands Network of Economics (NAKE). In addition, she assisted a PhD course on Spatial Econometrics at the Agricultural Economics and Rural Policy Group. She also worked at IFPRI as a visiting researcher in 2010. In 2011 and early 2012, she worked at the World Bank on Women Entrepreneurship Development Program, where she was consulting on cluster development in Ethiopia. She has presented her works in several international congresses during the Ph.D study period. In the process, she managed to publish some of her PhD researches in internationally reviewed journals like *World Development, Journal of Development Studies and Agricultural Economics*. She is a member of various professional associations including the Ethiopian Economic Association, the International Association of Agricultural Economists, and the European Association of Agricultural Economists. She is also an occasional reviewer of scientific articles for the *Agricultural Economics* journal of the International Association of Agricultural Economists.

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