Activity Choice in Rural Non-farm Employment (RNFE): Survival versus accumulative strategy

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Survival versus accumulative strategy

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Abstract

This paper examines the nonfarm employment choice of individuals using panel data from Ethiopia that covers the period 1994-2004. Non-farm activities that require more resources in the form of skill or capital yield higher returns but employ proportionately fewer people. Women have lower participation rate than men, and those women who participate are often engaged in low-return activities. The econometric results suggest that the factors that influence individuals' decision to participate in non-farm employment differ for the different types of activities. Determinants of participation in high-return activities are dominated by capacity variables. Determinants of participation in low-return activities are dominated by push factors. Education is the only factor that has the same (positive) impact on the likelihood of participation in all types on non-farm employment. Education was also found to have more impact on participation of women.

Keywords: Non-farm, off-farm, non-agriculture, income diversification, Ethiopia

1. Introduction

There is an increasing recognition in the literature that agriculture is not the only important sector in the rural economy. Studies in different developing countries have shown that the non-farm sector contributes a significant share to employment and income in rural areas (Ellis, 1998, Lanjouw and Lanjouw, 2001, Haggblade et al., 2007, Davis et al., 2010). Nonfarm activities account for 30% of full-time rural employment in Asia and Latina America and 10% in Africa (Haggblade, 2007). These figures do not include farmers who engage in nonfarm activities as part-time employment or during agricultural slack seasons. When these are considered, the participation rates are 83% for Asia, 82% for Latin America and 78% for Africa (Winters et al., 2009). The size of nonfarm employment is reflected in the level of income rural households earn from it. On average, the share of nonfarm income in households' total income is reported to be around 50% in Asia and Latin America and 35% in Africa (Reardon et al., 2007).

Most studies of income diversification tend to treat nonfarm employment as a homogenous group of jobs regardless of the type of employment or the degree of skill and investment required. However, this kind of aggregation can lead to misleading inferences about issues like determinants of nonfarm participation. It is not realistic to assume, for example, that factors that influence one's participation decision in casual labor are the same factors that influence the decision to engage in a lucrative business. Recent studies that disaggregate nonfarm employment between wage employment and self employment documented that the determinants of participation and the returns from the respective employments are not the same (Barrett, 2005, Woldenhanna and Oskam, 2001, de Janvry and Sadoulet, 2001, Corral and Reardon, 2001, Shi et al., 2007).

But what is largely missing from the literature is a more refined disaggregation of nonfarm employment that goes beyond functional classification to reflect also the level and quality of resources required and the sophistication of production activity involved. Lanjouw's (2001) classification of nonfarm employment into 'high productivity' and 'low productivity' activities, based on earnings from the activities relative to farm labor, gives an important distinction. However while recognizing the productivity difference among activities, this classification ignores the functional classification and considers wage and self employment activities with similar 'productivity' as comparable. A similar study in Kenya (Lay et al., 2008) distinguishes between high-return and low-return activities but used an ad hoc criteria to group activities as such. We believe that, for a better understanding of nonfarm employment patterns, it is important to disaggregate activities into wage employment and self employment and recognize the differences in resource requirements within these broad groups.

This paper assesses choice of nonfarm activity using panel data that cover 10 years in six survey rounds. We analyze individuals' decision to choose among four types of nonfarm employment activities: skilled wage employment, unskilled wage employment, high investment business and low investment business. There are three important contributions of this paper. First, the disaggregated analysis enable us to test not only whether wage and self employment have different sets of determinants but also whether the capacity and incentive factors that influence participation decision differ for different types of wage employment and different types of self employment. Second, by using multinomial model we are estimating participation in the four nonfarm employment activities simultaneously. The use of panel model enables us to control for unobserved heterogeneity, at both an individual level and the household level. To our knowledge, there are no studies that control for multilevel unobserved heterogeneity in occupational choice model. And third, the paper uses panel data that cover a relatively long period and wide variety of cultural, economic and agro-ecological conditions in rural Ethiopia making the sample more representative than found in most studies.

Several studies in developing countries found positive relationship between nonfarm participation and the income or wealth of the household (Reardon, 1997, Reardon et al., 2001). We found that the relationship between nonfarm employment and wealth or income of the household is not uniform across activities in Ethiopia. Participation in skilled wage employment and high-investment business increases with wealth while the opposite holds for unskilled wage employment and low-investment business. We also found that women are relatively heavily represented in low-return activities.

Comparing determinants of wage and self employment, we found that education is more important in wage employment and wealth, as given by land holding, is more important in self employment indicative of the type of resource relevant in the two groups of activities. However we also found that there are similarities between activities with comparable level of resource requirement regardless of functional classification. We found that activities with high resource requirement- skilled wage employment and high investment business- bring higher returns but employ significantly fewer individuals. While the determinants of these high paying activities are dominated by capacity variables, that of low paying activities are dominated by push factors.

Among the set of incentives and capacity variables that affect participation in nonfarm employment, education is the most important. It positively influences participation in all types of nonfarm employment. Women are more likely than men to participate in low paying nonfarm activities but educated women are more likely than men to participate in skilled wage employment. Thus education especially affects the quality of nonfarm employment prospects for Ethiopian women.

The rest of the paper is organized as follows. The second section discusses the conceptual framework and relevant literature followed by overview of the data and descriptive statistics in section 3. In section 4 we present the econometric model and section 5 discusses estimation results. The final section presents concluding remarks.

2. Conceptual framework and literature review

2.1 Conceptual framework

In this paper rural nonfarm employment (RNFE) refers to employment outside of the agricultural sector in manufacturing or service sector irrespective of location, function or degree of processing involved. Preparing and selling food and beverages in one's own home (on- farm) is considered a nonfarm activity as is running a cafeteria in the neighboring village or working as an officer in the local administration (off-farm).

We can discuss choice of RNFE in the frame work of individuals' earning maximization decision that involves allocation of one's labor and capital resources into alternative activities. Such a decision involves a constrained optimization with a set of incentives that determine the return from the respective activities and a set of constraints that define the capacity of individuals to undertake the activities. This choice of diversification into nonfarm employment can be decomposed into two interdependent and simultaneous choices: (1) The decision as to whether or not to participate in nonfarm employment and (2) The decision on the type of nonfarm activity.

The set of incentive variables relevant in these choices can be grouped into two: push and pull variables. One set of push variables represent factors related to the poor performance of the agricultural sector as a sufficient and reliable source of income. Such factors include inter-seasonal and other transitory drops in farm income, chronic food insufficiency and fluctuations in farm income (Reardon et al., 2007). Another source of push variables are incomplete markets for factors, including but not limited to missing credit and insurance markets. In the absence of financial markets, individuals and households diversify to self-insure themselves and provide working capital (Barrett et al., 2001). The pull variables emerge from comparing earnings in nonfarm employment with earnings in farm employment. The most important pull variables are the returns to factors supplied in the nonfarm sector- wage or salary in nonfarm wage employment and profits in self employment. The higher the returns to labor and capital in nonfarm employment, the most attractive nonfarm employment will be compared to farming.

These wages and profits are themselves dependent on the demand for goods and services produced by the nonfarm sector. Anderson and Leiserson (1980) identified three sources of demand for rural nonfarm activities: (a) nonfood goods and services for the rural population, which rise with rural income levels ; (b) inputs and services to agriculture which rise with agricultural development; and (c) manufactured and handicraft goods, stemming from external markets in other regions or abroad. An increase in demand from any of these sources directly increases the market and possibly the profit for self employment activities. It also increases the derived demand, and possibly the wage, for labor in those sectors, although the labor demand response of enterprises may also be itself affected by owners' capacity (Randrianarisoa et al., 2009) .

The main capacity variables that affect nonfarm participation are the human, physical and financial capital. Individuals differ in their capacity regardless of the market structure, as we see for example in the difference between educated and uneducated individuals or between individuals who have some startup capital for business and those who do not. The physical and financial constraints are less of a problem in a well functioning market as one can finance a business by borrowing. However where markets are not functioning, one’s human, physical and financial capitals are not easy to augment and become binding constraints. This leads to different outcomes by different individuals facing the same incentives. This capacity limitation restricts resource-poor individuals and households to a few low paying activities, as is observed in many African countries (Reardon, 1997). What is more, according to Barrett, et al. (2005), in rural Africa heterogeneity is not limited to the constraints. There are also differences in the incentives that individuals and households face. Such differences may result from the observable ‘spatial variation in transaction costs and gross market prices’ and from less observable differences in the shadow prices of factors and goods across individuals. The implication of the heterogeneous incentives and capacities is that different individuals and households face different feasible sets of activities from which they can choose (Barrett et al., 2005). Hence, while those who have more options because of their capacity can choose the activity that maximizes their return and sets them on accumulation path, others who have limited choice in the nonfarm sector but need to complement the insufficient farm income may be relegated to residual activities with very low return and negligible prospects for longer-term accumulation.

Although disaggregating the factors influencing nonfarm participation decision into incentive and capacity variables is very helpful, we have to keep in mind that the distinction between the two is not always clear cut. Some variables such as land can be considered both an incentive variable, indicating farm potential, and a capacity variable indicating wealth. This paper examines how the different forces influence individuals’ nonfarm activity choice.

2.2 Literature review

There are several empirical studies on rural income diversification across developing countries. Because the focus of this paper is on the decision to participate in rural nonfarm employment and the choice of nonfarm activity, the relevant literatures are mainly those which deal with determinants of nonfarm employment. Most studies examine the determinants from the supply side (Reardon, 1997). Often such discussions focus on incentive variables with less attention to capacity issues (Reardon et al., 2007). Below we summarize the main determinants of nonfarm participation as identified in several empirical studies. The discussion draws heavily from the review of literature in Africa (Reardon, 1997) and Latin America (Reardon et al., 2001) as well as studies from three Asian countries- India (Lanjouw and Shariff, 2002) Bangladesh (Deichmann et al., 2009) and China (Shi et al., 2007).

Human capital: An important component of individuals' human capital is education. The impact of education on nonfarm employment is consistent across the regions. Several of the studies document that education increases participation in nonfarm employment and income from it. Recent studies in several African countries[1] also strengthen earlier findings reviewed in Reardon (1997) about the positive impact of education.

The age of the participant or the household head is another component of the human capital indicating work and life experience. Reardon's review of studies in Africa doesn't discuss the impact of age. However, recent studies in Ghana (Abdulai and Delgado, 1999), Tanzania (Lanjouw et al., 2001) and Mali (Abdulai and CroleRees, 2001) show that at younger age, participation increases with age of the individual or the household head (until 30-40 years), after which increase in age is associated with a decline in the probability and level of participation. The same trend holds for India with the negative relation starting only after age 50 while in China age is found to have a negative impact.

Gender of the individual or the household head may also affect participation. Women were found to be less likely to participate in rural nonfarm employment in Tanzania (Lanjouw et al., 2001), China (Shi et al., 2007) and India (Lanjouw and Shariff, 2002). However the findings in Latin America were not conclusive. In the studies reviewed by Reardon et al. (2001), the effect of gender is either not significant or is very different across studies.

Demographic factors: Household labor supply has a positive impact on participation across the studies. However, the presence of children or dependency ratio did not affect participation, even when the study distinguishes between labor supply by husband and wife (Abdulai and Delgado, 1999).

Access to infrastructure and proximity to towns and cities: There seems to be a consensus that participation increases with proximity to cities and towns and with better infrastructure. Reardon,

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[1] The studies include Lanjouw et al.(2001) in Tanzania; Abdulai and CroleRees(2001) in Mali; Abdulai and Delgado (1999) in Ghana and Matsumoto et al.(2006) in Kenya, Uganda and Ethiopia

et al. (2007) argues that sometimes access to urban centers compensates for a lack of private assets such as education. Those individuals' closer to urban centers have a higher probability of getting nonfarm employment and earn more even if they are not educated.

Agroclimatic conditions and the state of agriculture in the region: In Africa, local nonfarm income is higher in more favorable agroclimatic areas while migration is higher in unfavorable areas. Local nonfarm income also increases with the year's rainfall (Reardon, 1997). In Latina America, zones with dynamic agriculture were found to have a higher level of nonfarm income per capita (Reardon et al., 2007). A dynamic agricultural sector has production and expenditure linkages with the nonfarm sector that expand the demand for nonfarm goods and services. A village that has some kind of growth motor, whether agriculture or not, is most likely to see an increase in demand for nonfarm goods and services thereby increase in earnings in nonfarm sector (Reardon et al., 2007).

Farm income and liquidity: Evidences from across studies in Africa suggest that households, who experience a decline in farm income, either temporarily or as a long-term trend, adopt nonfarm employment as an alternative strategy (Reardon, 1997). Land holding, which indicates farming potential, is negatively correlated with the *share* of nonfarm income in Latin America, as those with more land have better farm income (Reardon et al., 2001). However, some of the same studies also found that the *level* of income from RNFE increases with land holdings. This is because land holdings affect not only the incentives but also the capacity to engage in nonfarm employment. Land holdings can increase access to credit, social capital and own-liquidity which are instrumental to access lucrative activities (Reardon et al., 2007). In India, individuals coming from higher land holding households are more likely to participate in nonfarm employment compared to farm wage employment (Lanjouw and Shariff 2002).

Credit market failure, particularly to purchase farm input, may also be one of the reasons individuals want to participate in nonfarm employment. Some studies in Africa document that farm households engage in nonfarm employment to obtain capital for farm investment (Reardon, 1997). While nonfarm activities can be a source of agricultural investment for rural household who have limited access to credit, missing credit markets can also hinder participations in activities that require initial investment (Barrett et al., 2001).

Hypotheses

There are two related hypotheses we want to test in this paper. (1) The returns to nonfarm employment vary markedly across activities. We argue that an activity with high resource requirement gives better returns. This is because in the absence of well developed markets, the high resource requirements serve as entry barrier to help maintain higher returns compared to low input employment, which is relatively open to all individuals and hence involves intense competition that will keep average returns down; (2) the determinants of employment in high-return activities and low-return activities are different. Economic logic implies that high-return activities are attractive for everyone. However, whether or not one engages in such activities depends on the capacity to satisfy the human and financial capital requirements of the activities. Hence capacity variables will be the most important factors for employment in high-return activities. On the other hand, individuals who are willing to work in low-paying jobs must be earning even less from agriculture or need the money from the nonfarm sector for liquidity reasons. Hence the most important determinants will be the push factors.

3. Data and descriptive statistics

3.1. Data

The empirical analysis in this paper is based on the Ethiopian Rural Household Survey (ERHS) data. The paper uses individual level data to analyze activity choice in nonfarm employment. We include only members of the household who are 15 years old and above. From these groups of individuals we excluded members who cannot work because of disability or other health problems. The descriptive statistics are based on this sample of adults, averaging more than 4500 in each survey year. The sample used in the econometric estimation includes only individuals who participated in nonfarm employment or farm wage employment.

Each survey round obtained information on income earned from various activities, including income from nonfarm activities and a set of questions on the individual and household characteristics. Information on wage employment and self employment activities are collected for the past four months. The sampling unit in the surveys is the household. However, for each activity, the labor supply (in days) and the payment received in cash and in-kind is reported at individual level. In-kind-payments[2] are converted to their cash equivalent using community level price data collected in the same period.

This is a unique set both in the period it covers and the variation within the sample. However the data also have important limitations. Although the data are rich in covering several topics, they were not collected with the intent of examining rural nonfarm activity. Hence the data miss few important details that interest us. For example, the labor supplied is given in days rather than hours and it was not always fully reported for all participants. In this paper an individual is said to be a participant in rural nonfarm employment if he or she supplied a positive number of labor days to the sector.

We used consumption expenditure and asset values to compare participation by income and wealth. The consumption expenditure variable refers to per capita expenditure on food and nonfood items. Households reported nonfood expenditure for one month. The food expenditure for a month is computed from a one week recall by multiplying the week's expenditure by 4.28. The values of food consumed from own production, in-kind payments and aid are computed using local prices. Consumption expenditure does not include purchases of household durables. For ease of averaging consumption expenditure across years the nominal values are deflated by consumer price index (base year 2000).

The asset variable used in the comparison refers to non-productive assets such as tables, chairs, radio, jewelry etc, so that households are compared on the value of assets they can all potentially own. Moreover, these assets are considered as the most important indicator of wealth in the study area (Bevan and Pankhurst, 1996). The value is based on the households' report on how much the assets will be worth in a local market. This is susceptible to reporting error, but given that we do not have information on asset prices and the details on the state of the respective assets, we believe that households' own evaluation is the best we can do. The asset variable has a positively skewed distribution. The median value of asset owned is ten dollars while five percent of households owned about an average of 460 dollars worth of asset.

[2] In-kind payments are typically reported in local units. These are converted into metric units using a conversion factor specific to each village that is computed based on the data in the community survey.

3.2. Rural nonfarm employment in Ethiopia: Some descriptive statistics

3.2.1. Definition and typology

The survey identified more than twenty types of nonfarm employment activities. Some of the activities are more common than others. Employment in Food-for-work projects, alternative fuel production[3] and petty trade are among the most common nonfarm activities, while very few people participate in traditional medicine or clerical work. There are both demand side and supply side issues at play. It may be possible that a small rural village of 500 households supports only one or two traditional healers or blacksmiths but can support tens of laborers. But, if the returns to labor differ markedly across activities, small number of participants may also signal entry barriers to the more lucrative activities.

To understand the determinants of participation better, we classify activities into different groups. First, using a broad functional classification of RNFE, we distinguish between self employment and wage employment activities. Then activities are further disaggregated into sub-groups based on the resource requirement in the respective activities. While there are different incentives and constraints for participating in different RNFE activities, it is likely that two individuals with the same incentives to participate may face different constraints depending on their human, physical, financial and social resources. The following tabulation shows the grouping between wage and self employment, and sub-grouping within these two based on skills required for wage employment and capital requirements for self employment.

	Low resource requirement	**High resource requirement**
Wage employment	<u>Unskilled</u>: e.g., food-for-work, other casual labor, working as guards or maid	<u>Skilled</u>: e.g. , teaching, administration, clergy, masonry
Self employment	<u>Low-investment</u>: e.g., homemade food, petty trade, handicraft	<u>High-investment</u>: e.g., livestock trade, transport by pack animals

[3] This refers to processing/production of dung cakes, charcoal and fuel wood for sale.

The proficiency required in skilled wage employment may be obtained through formal schooling or through informal training or apprenticeship on the job. In both cases, the skill is acquired over a period of time and involves the investment of time, money and social connections. In self employment, financial resources are the main requirement. In Ethiopia, the difference in capital requirement between the activities grouped in low investment business and high investment business is substantial. The median investment needed to enter into charcoal making, dung cake collection, handicraft production, weaving, or food processing is 0-20 birr (up to US$3) while for trading livestock, transport services and starting a shop require 300-500 birr ($45-80) (Dercon, 2002).

3.2.2. Returns from nonfarm employment

Table 1 shows the average daily return for labor in different nonfarm activities. The return from skilled wage employment is about three times as high as the return from unskilled wage employment; and the return for high investment business is twice that of low investment business. Unskilled wage employment is the lowest paying job and its return is the same as the return for labor in farm wage employment.

Averages are highly influenced by extreme values and cannot tell us whether one activity pays better than the other in most cases or if it pays highly only for few but with a very big margin. To investigate this better, we plot the cumulative frequency distribution of income from each of the nonfarm activities and test for first-order stochastic dominance.

As shown in Figure 1, skilled wage employment gives the highest level of income throughout the distribution with the graph much more distinct and further from the next high paying activity- high investment business- in the 60^{th} to 85^{th} percentile range. Both skilled wage employment and high investment business first order stochastically dominate unskilled wage employment and low investment business. The cumulative distributions of incomes from low investment business and unskilled wage employment are not distinct. Hence we cannot rank between the two based on first-order stochastic dominance tests. The two low paying nonfarm activities have a close distribution to farm wage income, however they slightly first order stochastically dominate farm wage income.

From Figure 1, we learn that for any individual maximizing earnings, skilled wage employment is more attractive than all other activities followed by high investment business. Hence, if an individual chooses unskilled wage employment or a low investment business, it must be because they did not have the capacity to engage in better paying skilled wage employment or high investment business. Farm wage labor is the least attractive work in terms of its earnings distributions which helps explain why people routinely try to move into nonfarm employment.

3.3. **Participation in rural nonfarm employment**

3.3.1. Households

On average 35%[4] of the households in the panel participated in rural nonfarm employment. Other studies looking into nonfarm employment gave average participation rate different from this and from each other. In Tigray, Woldenhanna and Oskam (2001) reported an 80% rate of participation while in Oromia only 25% participated in nonfarm employment (van den Berg and Kumbi, 2006). The big difference between these rates may indicate the structural difference between the economies in these two agroecologies. There are several food-for-work projects in Tigray that serve as an important source of nonfarm employment. Infact, 58% of the households in the sample in Woldenhanna and Oskam's study were engaged in FFW.

Of those who participate in nonfarm employment activities, 70% participate in self employment and 41% in wage employment. One in six of nonfarm participant households (about 13%) choose both wage and self employment. About 11% of households participated in a portfolio of activities such as combining two types of wage employment, two types of self employment or wage employment and self employment. However, only 5% of nonfarm participant individuals are involved in such a portfolio. This shows household level pluriactivity along with individual level specialization in nonfarm employment.

The literature on nonfarm diversification in Africa documents a positive correlation between wealth or income of households and participation in nonfarm employment, especially with regard to lucrative nonfarm activities (Ellis, 1998, Lanjouw et al., 2001, Reardon, 1997,

[4] This rate is based on participation by adult members only. The rate based on households' participation regardless of age of participant gives us a higher rate (40%).

Woldenhanna and Oskam, 2001). Table 2 reports households' participation in the different nonfarm employment activities in each consumption expenditure tercile. If we compare the total number of participants in each tercile (the last row in the table) without making any distinction among the different types of activities, we see no positive correlation between nonfarm employment participation and expenditures. Rather, the number of nonfarm participants is higher in the lowest one-third of the distribution.

The activity disaggregated participation numbers reveals a different pattern, however. For skilled wage employment and high investment business, more people in the higher tercile participate while for unskilled wage employment and low investment business, participation decreases as one move up the expenditure distribution.

The table also shows the average (non-productive) asset holding for households engaged in each activity. We can see that households who participate in the high paying activities have higher asset levels than those in the low paying activities. The average asset holdings of those engaged in skilled wage employment is more than double of those engaged in unskilled wage employment. Hence, in the Ethiopian context, nonfarm participation is not correlated uniformly with income and wealth. It has a positive correlation for skilled wage employment and high investment business and a negative one for unskilled wage employment and low investment business.

3.3.2. Individuals

Because we are examining participation decision by individuals, the units of analysis for the rest of the paper are adult members in the household. There are, on average, three adults per household. While 65% of the households did not have a single member participating in nonfarm employment, for some households more than one adult was involved in the nonfarm sector. Although the proportion of women in the total adult sample is slightly higher than men (51%), their share in rural nonfarm employment is much lower (36%). Women are relatively heavily represented in low paying activities. Almost half of the participants in low investment business are women, compare to only 7% in skilled wage employment.

Occupation versus participation in nonfarm employment

In terms of vocation, the majority of adults are either primarily farmers (36%) or home makers, who take care of the household chores and may sometimes help in the farm (40%)[5]. Only around six percent of individuals reported that their primary occupation is in a nonfarm sector. As Table 3 shows the most common nonfarm occupations are: trade, manual labor, craftsmanship and business in homemade food and beverage. Although only six percent of individuals have a nonfarm primary occupation, the share of participants in nonfarm employment in any year is typically higher. On average, 13% of adults in the sample participated in nonfarm employment. In developing countries, participation figures for nonfarm activities are typically higher than the corresponding employment figures based on occupation (Anderson and Leiserson, 1980, Winters et al., 2009). This discrepancy is because of two reasons. First, nonfarm employment is a secondary occupation for many individuals who engage in nonfarm activities seasonally or as part-time job. Second, individuals' decision to participate in nonfarm employment in a particular year may differ from their long run occupational choice. For example, an individual who is a farmer or a student by vocation may decide to participate in nonfarm wage employment in a particular year because of an agricultural shock that affected the household income.

Participation by employment type

The number of participants in each year in the different nonfarm activities and the relative share of each activity in total nonfarm employment are given in Table 4. The greatest participation, more than half, is in low investment business, followed by unskilled wage employment. The employment share of high investment business and skilled wage employment is less than 10 percent each. The ranking of activities based on returns as given above is inversely related with the ranking based on employment share. The employment share of the highest paying activity (skilled wage employment) is about one-fifth of the employment share of the least paying activity (unskilled wage employment). The two least paying activities account for 88% of nonfarm employment.

In the six rounds of the survey, the least number and share of adult participation is observed in 1997, corresponding to low participation rate in unskilled wage employment and low investment

[5] More than 93% of the self identified farmers are men and almost all of the home makers (about 98%) are women.

business. The year 1997 brought good rainfall compared to the other periods. The fact that participation did not decline in high investment business and actually increased in skilled wage employment when the low paying activities show a marked decline in this period indicates that push factors are the driving force behind participation in low return activities. When on-farm agricultural returns are good, rural Ethiopians rely less on low-return nonfarm activities.

Some individuals participated in more than one type of nonfarm activities. Table 5 gives the proportion of individuals in each type of nonfarm employment that participated in multiple activities. Compared to other activities, more individuals in high investment employment engage in multiple nonfarm activities even though fewer individuals engage in high investment business itself. It seems that once an individual decides to engage in high investment business, there may be economies of scale or scope that makes a portfolio of activities more attractive than pure specialization. Moreover, compared to skilled wage employment (the activity with the second highest share in multiple activity), high investment business may be less structured in its time demands. Another reason may be related to capacity. A person who has the financial resources to engage in high investment business will also be able to participate in other activities. In Kenya, for example, wealthier households were found to engage both in low-return and high-return activities while the poor engaged only in low-return activities (Lay et al., 2008).The fact that low investment business is the main nonfarm activity simply reflects its low resource requirement.

4. Econometric model

We formulate an individual's choice among alternative employment options in a random utility framework. Let U_{ijt} denote, utility of individual *i* associated with an employment activity *j* at time *t*. The random utility model assumes that utility is a random function, either because of imperfect optimization by the individual or because the analyst has incomplete information (Maddala, 1983, McFadden, 1973, 1974). Hence utility U_{ijt} is given by:

$$U^*_{ijt} = \mathbf{X}_{it}'\beta_j + \varepsilon_{ijt} \qquad (0.1)$$

X is a vector that denotes characteristics of individuals (age, sex, education etc) which vary across individuals and over time. The coefficients are different for each alternative. The error term $\boldsymbol{\varepsilon}_{ijt}$ reflect uncertainty in the random utility model. Given, this latent variable, we can define an indicator variable *D* which links the expected utility from different activities with the employment choice made. For each individual *i* and activity *j*, the indicator variable D_{ijt} is observed.

$$\begin{aligned} &D_{ijt} = 1 \;\; if \;\; j = \arg\max U^*_{ijt} \in \left\{ U^*_{i1t}, U^*_{i2t} .....U^*_{iJt} \right\} \\ &D_{ijt} = Otherwise \end{aligned} \tag{0.2}$$

What we are eventually interested in is how a change in the independent variables affects the activity choice. If we assume that the error terms are independently and identically distributed with a type I extreme-value distribution, we get the choice probability model. According to McFadden (1973), only the i.i.d., type 1 extreme value (Gumbel) distribution produces a probabilistic choice model that is consistent with utility maximization. And the resulting choice model is multinomial logit model. Our panel multinomial logit model can be given as:

$$pr(Y_{ikjt} = 1) = \frac{\exp(\mathbf{X}_{ikt}{}'\beta_j + \mathbf{Z}_{kt}\mu_j + \alpha_i + \eta_k)}{\sum_{j=1}^{5} \exp(\mathbf{X}_{ikt}{}'\beta_j + \mathbf{Z}_{kt}\mu_j + \alpha_i + \eta_k)} \tag{0.3}$$

X_{ikt} refers to characteristics of individual *i* in household *k* at time *t* (gender, age, education etc.). Some of these variables, such as gender, are time invariant and others, such as age are time varying. The vector Z_{kt} refers to household level variables (land owned, total labor endowment, etc.). The terms α_i and η_k capture unobserved individual and household heterogeneity, respectively. The unobserved effects are assumed to have each a normal distribution and to be mutually independent, and independent of the error term. We estimate the occupational choice model for individuals who work off-farm. We have four choices in nonfarm employment: nonfarm skilled wage employment, nonfarm unskilled wage employment, high investment business, low investment business. A fifth choice-farm wage employment-is used as a comparison. In estimating a multinomial logit model, the coefficient vector and heterogeneity term of the base category has to be set to zero for identification of the model. We used farm employment as the base category so that all nonfarm occupations will be compared with the alternative off-farm employment in the rural economy.

Because the marginal likelihood of such models does not have a closed form, and hence no analytical solution, the maximum likelihood estimation typically involves integral approximation, in our case by Gauss-Hermite quadrature. Our model is estimated using the STATA program GLLAMM[6].

Variables in the empirical model

In line with the theoretical discussion above, we included two sets of explanatory variables for estimation: incentive variables and capacity variables. It is not easy to get several variables that directly represent the incentive factors. This is because the price data in nonfarm employment are not typically available and many of the individual and household level variables that reflect the push factors, such as farm income, asset holdings and credit, may be endogenous. Having said that, we discuss below the variables we have chosen at a household and village level that directly or indirectly capture the pull and push factors. Table 6 provides exact definitions and descriptive statistics of all of these variables.

At a household level we include the land holdings[7] both as an incentive and a capacity variable. Land holdings capture food sufficiency in farming whereby household with more land can more easily live on the output and income from farming. Hence, we expect land holdings to be negatively associated with participation in nonfarm employment. However, because land holdings also indicate wealth, higher land holdings may be associated with better access to capital which increases the capacity to participate in nonfarm employment, especially self employment. Larger land holdings may also be associated with higher crop income, which can help finance startup capital. Reardon et al. (2007) termed this opposing effect of land on nonfarm participation, 'micro paradox'. We may get different impacts at different land holding levels because either the incentive effect or the capacity effect dominates. We include both land per capita and the squared term to allow for a nonlinear relation.

At a village level, the incentive variables include rainfall level and variability, household average consumption expenditure, population density and a dummy variable for villages with net

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[6] See appendix for further discussion.

[7] Land holding can be considered exogenous since purchase and sale of land is illegal in Ethiopia (the state owns the land) although one may cultivate more or less than they 'own' through different rent arrangement

immigration. We expect individuals in agriculturally favorable areas with high rainfall and low output risk (as captured by rainfall variability) to have less incentive to participate in nonfarm activities. High consumption expenditure reflects the purchasing capacity in the village, hence the demand for nonfarm goods and services, as well as the capacity of individuals coming from this village to satisfy the resource requirements in nonfarm employment. Hence it can be expected to have a positive influence on nonfarm participation. On the other hand, individuals in rich villages may have less (push factor) incentive to engage in nonfarm activities, particularly in low paying activities. The effect is ambiguous for low paying activities but for high paying activities, it can be expected to have a positive effect. We expect individuals coming from village with positive net immigration to be more likely to participate in nonfarm employment because of increased land pressure. The impact of high population density is to increase likelihood of participation in nonfarm employment. It may be interpreted as a push factor if land fragmentation reduces agricultural production or a pull factor if we consider the market potential associated with densely populated areas. Or it may be that both factors are at work.

The capacity variables include: the number of adults in the household, education variables and distance to the nearest town. We have four education dummies: informal literacy, literacy through less than six years of formal schooling, elementary education and high school education or above. The comparison group has no education. We expect all types of education to have a positive impact on nonfarm employment participation. Education increases the willingness and the ability to supply labor to nonfarm employment. Education improves the value of labor of the educated individual making it more costly for the household to keep it at home or in low paying farm employment, and it increases the individual's potential to acquire and utilize relevant employment information. Education also increases access to nonfarm employment by signaling higher labor productivity and by improving individual's network potential. This is true even for unskilled employment because education may be used as a selection mechanism to ration jobs in a situation where there are fewer jobs than potential workers. We expect that the impact of education will be more pronounced as one move up the education ladder.

Access to education and particularly high school education is poor in rural Ethiopia. One in five villages has no school at all and only one of the villages in the whole sample has a high school. This implies that going to school involves long distance walk (from 2-25km) or staying in town (boarding in group). This puts girls in the disadvantaged position not only because long distance walks and staying away from family are frowned up on but also because compared to boys and men, women and girls spend more time working at home with less time for schooling. Only 18% of all adult women in the sample have some level of formal education compared to almost 40% of men. We include multiplicative term between gender and education, to test whether formal education has additional impact on women.

Individuals coming from households with larger adult labor supply are expected to be more likely to participate in nonfarm employment because of the possibility of other members sharing or fully taking care of the farming and household responsibilities (Barrett and Clay, 2003). Distance to the nearest town captures both the effect of transaction cost and access to wider markets. Individuals who live closer to urban centers have relatively lower job search cost and have access to a wider market if they own a business. We also include multiplicative term between education and distance in order to see if education differentially affects the prospects of individuals who come from villages far from town centers.

The individual level characteristics include: age, gender, and dummies for student and head. We also included age-squared to capture potential life cycle effect. Theory and literature does not suggest a particular direction for the impact of age and gender on RNFE. It may be that age, as an indirect measure of experience, increases access to nonfarm opportunities. On the other hand, as individuals in a farm household get older, they may have less interest in nonfarm employment. With regard to gender, Ellis (1998) argues that women have less access to nonfarm employment than men. This is either because of a direct cultural prohibition to engage in certain activities or an indirect limitation through less time available for women who are busy with domestic duties. However, the participation outcome may also depend on the type of employment examined. It may be easier, for example, for women to combine domestic activities and business in food and beverage production, while the same cannot be said about casual off-farm labor, hence the effect is ambiguous.

To control for the possibility of seasonality influencing the participation pattern observed in the different rounds, we include a 'survey date' variable which indicates the time gap between the peak rainy season and the survey dates for each village in each round. We also include time dummies, round2-round6, corresponding to the different years of the survey for a time-fixed effect.

5. Estimation results and discussion

The estimation results from the random effects multinomial logit model are given in Table 7. Our estimation controls for heterogeneity both at individual and household levels[8]. We found significant unobserved individual and household heterogeneity. The intra-class correlations at individual and household levels are respectively, 0.6 and 0.34. In a multinomial model, the parameter estimates on choice ***j*** are interpreted as the change in the log-odds between the outcome ***j*** and the base category for a unit change in the predicator given other variables in the model are held constant. The magnitude of coefficients in a multinomial model are difficult to interpret directly (Wooldridge, 2002), but the sign and size of the coefficients will be enough for our purpose to compare the relative importance of explanatory variables in influencing choice outcomes. For example the log-odds for skilled wage employment relative to farm wage employment are 4.4 higher for individuals with high school education compared to those who have no education. The log-odds are only 1.1 higher for those with less than six years of schooling[9].

If we compare the size of coefficients and significance level of explanatory variables across functional classification, we see some general differences between wage and self employment. Wealth, as given by land holdings, has more impact on self employment than on wage employment indicative of the importance of access to start up capital for self employment. Agroecological variables are also more important in self employment which shows the importance of farm-nonfarm linkages. On the other hand, education is more important in wage employment than self employment.

Within wage employment, there are differences between skilled and unskilled wage employment. In skilled wage employment, the coefficients on all types of education are positive

[8] To test for robustness, we estimate a pooled multinomial logit that control for clustering at individual level. The results were generally very similar to the results reported here. But because we sacrifice the panel controls in the pooled model, the model underperforms the panel multinomial.

[9] One can also report this in terms of odds ratio ($e^{\beta j}$) which show the proportionate change in relative risk of choosing activity j rather than farm wage when x_i changes by one unit.

and statistically significant with the impacts increasing as one move from literacy up through secondary education. Education positively influences participation in unskilled wage employment too but only for those who have at least completed elementary education. Even then, the coefficients are much smaller than those in skilled wage employment. Women are more likely to participate in unskilled wage employment while gender does not affect participation in skilled wage employment. On the other hand, the interaction term between gender (female=1) and formal education is positive and significant for skilled wage employment indicating that the impact of formal education on participation in skilled wage employment is higher for women than men. There is no equivalent gender premium to education's effect on participation in other nonfarm employment activities. Land holdings positively influences participation in skilled wage employment. This shows that those who have the capacity to accumulate human capital and cover the transaction costs related with job search and employment are better positioned to engage in skilled wage employment. At very high levels of land holding, however, households may choose to specialize on farming. Unskilled wage employment is not affected by land holding.

Agroecology does not affect skilled wage employment, indicating that skilled wage employment does not respond to what happens in the agricultural sector. On the other hand unskilled wage employment responds negatively and significantly to mean rainfall. Individuals who live in places with good agricultural potential are less likely to participate in unskilled nonfarm wage employment as are individuals who come from well-off villages. Both of these refer to push factors. The immigration variable, which indicates the dynamism of the village, is positive and significant for skilled wage employment which may result from a demand side effect where a dynamic economy has more skilled job, or a supply side which indicate that there will be more skilled people in such villages. Unskilled wage employment fluctuates across the years while skilled wage employment does not. The log-odds of participating in unskilled wage employment is higher most of the years compared to the reference period (1997) which had better agricultural performance because of good rainfall. Individuals are also more likely to be observed in unskilled wage employment, the further is the survey from the peak rainy season. Both of these indicate that participation in unskilled wage employment is more likely when agriculture is not doing well. None of these are significant for skilled wage employment.

To summarize the determinants of skilled versus unskilled wage employment, we found that determinants of participation in skilled wage employment are dominated by capacity variables while unskilled wage employment is dominated by incentive variables and particularly those related to push factors.

Similarly, there is some difference between the determinants of the two types of self-employment. Age is important in self employment indicative of the relevance of experience in business activities. However, there is higher threshold for high investment business (43) than low investment business (26). Education positively influences participation in self employment. While only high school education is significant in high investment business, in low investment business individuals who completed elementary education are also more likely to participate. Students are less likely to participate in high investment business while individuals who come from household with more adult labor are more likely to participate. Both of these indicate the higher time demands in high investment business in terms of time and experience. One of such activities, cattle trade, may involve being away from the village for several days.

Initially, participation in both types of self employment increases with land holdings. Households with relatively smaller land holding and those with limited farm income seek to diversify into nonfarm employment; for such households an increase in land holding indicates an increase in wealth which will enable them to obtain the capital necessary to engage in nonfarm employment. The negative coefficients on land square imply that at very high level of land holdings households afford to participate in nonfarm employment but may choose to specialize in farming.

Individuals, who live in agriculturally risky areas, as captured by the variance of rainfall, are less likely to participate in both high investment business and low investment business relative to farm wage employment. This may indicate the importance of farm-nonfarm linkages. The main self employment activities- food processing, grain trade, millings depend on agriculture for both input supply and consumer demand. Unreliable input supply and unstable output demand is not conducive for business activities. Surprisingly, high investment business also responds negatively to mean rainfall. The negative coefficient may indicate that in agriculturally favorable areas those capable of participating in high investment business may specialize in farming. The coefficient for population density, which captures farm land scarcity in the village (push factor) but at the same time reflects the market potential for products and services produced by the nonfarm sector (pull factor), is positive and significant for high investment business. Individuals coming from a village with net immigration are less likely to participate in low investment business relative to farm wage employment probably because the village is exposed to more competitive products from urban areas. Relative to the reference year, participation in low investment business is higher in three of the five years indicating fluctuation as a response to agricultural production.

Comparing the determinants of the high and low investment business, we see that although incentive variables are important in both types of self employment, determinants of high investment business are dominated by capacity variables.

The factor that has a consistent impact across all nonfarm activities is education. Education positively influences participation in nonfarm employment relative to farm wage employment. This is in line with earlier findings in several developing countries as discussed in the literature review. The differential impacts of education by gender we have found for skilled wage employment have also been documented in some other countries. In comparing nonfarm participation by married men and women in Ghana, Abdulai and Delgado (1999) found that the marginal effect of a year of female schooling is higher for women than men. In Mexico de Janvary and Sadoulet (2001) found a larger nonfarm participation-inducement effect of education for women. We have also found that controlling for other factors women are significantly more likely to participate in low-paying nonfarm activities. This may be a result of the low entry barrier in terms of skill and capital in those occupations that makes them accessible to women. This finding is also consistent with results from Ecuador (Lanjouw, 1999) and Brazil (Ferreira and Lanjouw, 2001).

6. **Conclusion and policy implications**

This paper examined the different incentives and constraints that guide individuals' choice of nonfarm employment activities in Ethiopia. By disaggregating nonfarm employment into different types of wage employment and self employment, we were able to test whether the factors affecting participation differ among alternative nonfarm activities. The use of panel data allowed us to control for unobserved heterogeneity both among households and among individuals within households.

We found that activities with higher resource requirement- skill wage employment and high investment business- yield more attractive returns per unit of labor. On the other hand these activities employ far fewer individuals. There appear to be important entry barriers to accessing the most attractive occupations in rural Ethiopia. We also found that women were more likely to participate in unskilled wage employment and low investment business, the nonfarm sectors with the lowest entry barriers.

We also found that the most important determinant of nonfarm participation is education. Educated individuals are more likely to participate in all types of nonfarm employment. But especially for skilled wage employment, education matters enormously and it has even more impact on participation of women.

When we compare determinants across different types of nonfarm employment, we can see that determinants of participation in low return activities is dominated by push factors such as low or insufficient income. And participation in high paying activities is dominated by capacity variables such as education and labor availability.

Our findings on the determinants of high paying activities versus low paying activities imply two paths for nonfarm participants. Those who are employed in unskilled wage employment and low investment business earn returns close to farm wage employment. They choose these activities for survival reasons. Because they are not likely to save and accumulate much from their nonfarm income, ceteris paribus, these activities remain the only nonfarm employments to which they have easy access. On the other hand, those who have the capacity to engage in high-paying activities such as skilled wage employment enjoy superior returns and put themselves on an accumulative path. Hence policies that seek to promote RNFE as a way out of poverty should recognize the different types of activities with different outcomes. Enhancing the asset endowments and particularly education may improve the poor’s access to nonfarm employment activities that provide upward mobility.

*Table 1: Daily returns for labor in RNFE (in Birr)**

RNF activity	Mean	Std. Err.
High investment business	20.2	6.5
Skilled wage employment	15.1	2.5
Low investment business	8.9	0.8
Unskilled wage employment	5.4	0.7

*This refers to real daily income in 2000 prices. The average is calculated for the pooled data but standard error is controlled for clustering.

Table 2: Households' nonfarm participation by expenditure tercile and wealth tercile

Type of nonfarm employment	Lowest (2838)	Middle (2838)	highest (2837)	Employment share	Value of assets	
					mean (Birr)	Std.Err
Skilled wage employment	81	80	111	0.09	539.9	173.0
High-investment business	126	133	157	0.13	362.5	98.3
Low-investment business	783	639	561	0.64	305.3	28.4
Unskilled wage employment	436	370	301	0.36	113.4	23.5
RNFE participant	1183	1034	920	1*	273.5	23.7

The number of participants and the shares are based on the pooled sample. The values of assets refer to initial level of asset (1994a). *The column sum is not equal to one because some of the households participated in more than one activity.

Table 3: Number of adults whose primary occupation is a nonfarm employment

Type of RNF occupation	1994+	1994++	1995	1997	1999	2004
Trader	128	127	130	104	57	79
Construction worker (Builder/Mason/Carpenter, etc.)	38	39	39	32	44	49
Craft worker/Potter	38	39	40	35	14	24
Homemade food &beverage Production and sale (*Tella/Tej/Injera*)	36	37	38	27	12	6
Soldier	29	30	30	8	5	2
Party official/Administrator/Clerical	17	17	17	7	3	13
Skilled (factory) worker	16	17	17	10	7	1
Teacher	16	18	18	11	6	6
Weaver	12	12	12	15	6	1
Driver/Mechanic	10	10	10	4	3	2
Blacksmith	4	4	4	4	3	5
Health worker	2	2	2		1	1
Others	8	9	11	8	26	25
Number of adults with nonfarm occupation	354	361	368	265	187	214
Share of adults with nonfarm occupation	0.07	0.08	0.08	0.06	0.04	0.05

+, ++, 1994a and 1994b refer to the two rounds in the early and later part of the year in 1994, respectively.

Table 4: The number of nonfarm employment participants by type of activity and year

	Skilled wage employment	Unskilled wage employment	High investment Business	Low investment business	Multiple activities	Proportion of participants in RNFE*
Survey year						
1994a+	44	227	46	582	16	0.18
1994b++	46	192	65	334	29	0.13
1995	44	236	45	276	22	0.12
1997	58	112	60	145	8	0.08
1999	44	208	45	381	47	0.14
2004	16	229	51	276	60	0.14
Panel average						0.13
Number	42	201	52	332	30	
As share of RNFE	0.07	0.33	0.09	0.55	0.05	

+, ++, 1994a and 1994b refer to the two rounds in the early and later part of the year in 1994, respectively.
*the sample is total number of adults in the work force

Table 5: Proportion of participants in multiple nonfarm employment: by type of nonfarm activity

Type of nonfarm employment	Proportion of individuals who have also participated in:				
	Skilled wage	Unskilled wage	High investment business	Low investment business	Multiple employment
Skilled-wage employment		0.02	0.02	0.08	0.12
Unskilled-wage employment	<0.01		0.01	0.10	0.11
High-investment business	0.01	0.05		0.14	0.20
Low-investment business	0.01	0.06	0.02		0.08

Table 6: Variable descriptions

Variable	Description	Mean*	Std.Dev
Age	Age of the individual	37.67	14.09
Female	male=0, female=1		
Informal literacy	individual got the education from religious training or literacy programme=1, =0 otherwise	0.06	0.24
Formal schooling	The individual has gone to school but did not complete elementary school=1, =0 otherwise	0.18	0.38
Elementary/Junior high	The individual finished elementary school (six years) and may have attended Junior high school(grade 7 & 8) =1, =0 otherwise	0.10	0.30
High school /above HS	The individual has attended a high school or above	0.05	0.23
Household head	the individual is household head	0.62	0.49
Student	the individual is a student	0.03	0.16
Land pc	Per capita land holding in hectares	0.25	0.38
Adult members	the number of adult members of the household	3.40	1.96
Distance to town	Distance to the nearest town from the village (in Km)	10.56	6.80
Rainfall CV	Variability of rainfall in the village. Coefficient of variation	0.20	0.09
Rainfall Mean	Mean village rainfall (based on 1995-200 data)	1061.79	264.33
Village cons. expenditure	the average household consumption expenditure (in Birr) in the village	426.09	228.68
Net immigration	=1 for villages with more people moving in to the village than leaving, =0 otherwise	0.30	0.46
Population density	population density in 1994 in the district	192.01	109.24

***N=2460 for all except adult members (2452) and land pc (2447)**

Table 7: Estimation result for multinomial logit model: A three level random intercept model

Coefficients	Skilled wage employment		Unskilled wage employment		High investment business		Low investment business	
	Coefficients	p-values	coefficients	p-values	coefficients	p-values	coefficients	p-values
Age	0.102	0.109	-0.040	0.430	-0.086	0.145	-0.052	0.287
Age2	-0.001	0.327	0.001	0.367	**0.001**	0.092	**0.001**	0.097
Female	-0.566	0.499	**1.853**	0.000	0.588	0.300	**2.751**	0.000
Informal literacy	**1.114**	0.061	0.255	0.641	-1.317	0.142	0.496	0.359
Formal literacy	**1.548**	0.027	0.815	0.170	0.343	0.609	0.812	0.160
Elementary/Junior high	**2.534**	0.000	**1.674**	0.006	0.699	0.320	**1.661**	0.006
High school /above HS	**4.436**	0.000	**2.387**	0.003	**1.576**	0.078	**2.366**	0.003
Household head	-0.119	0.789	0.184	0.624	0.695	0.122	-0.071	0.848
Student	-0.479	0.578	-0.746	0.288	**-1.678**	0.090	-0.796	0.250
Land per capita	**1.810**	0.032	0.284	0.703	**2.274**	0.020	**2.340**	0.001
Land pc2	**-0.812**	0.023	-0.423	0.189	**-1.410**	0.011	**-1.167**	0.000
Adult members	0.047	0.590	0.090	0.240	**0.168**	0.050	0.103	0.169
Distance to town	0.054	0.176	0.051	0.108	-0.014	0.702	0.037	0.228
Rainfall, CV	-3.382	0.121	-0.699	0.711	**-8.327**	0.001	**-12.615**	0.000
Rainfall, Mean	-0.001	0.159	**-0.002**	0.004	**-0.002**	0.046	0.000	0.772
Average consumption exp.	0.000	0.816	**-0.001**	0.041	0.001	0.216	0.000	0.675
Net immigration	**0.934**	0.022	0.250	0.480	0.369	0.370	**-0.934**	0.008
Population density	0.001	0.770	-0.002	0.400	**0.006**	0.004	0.001	0.546
Female X schooling	**3.528**	0.028	1.416	0.300	1.561	0.319	1.459	0.278
Distance X schooling	-0.048	0.381	-0.040	0.384	0.046	0.398	-0.008	0.851
Survey month	0.019	0.834	**0.191**	0.013	-0.107	0.254	-0.054	0.472
R1(1994a)	-0.330	0.521	0.632	0.140	-0.841	0.110	**0.725**	0.078
R2(1994b)	-0.468	0.342	-0.517	0.220	0.011	0.983	0.613	0.147
R3(1995)	0.374	0.509	**1.837**	0.000	-0.119	0.830	**0.751**	0.100

R5(1999)	0.310	0.478	**1.052**	0.005	0.333	0.445	**1.321**	0.000
R6(2004)	-0.839	0.149	**1.713**	0.000	-0.292	0.566	**0.710**	0.098
Constant	-2.366	0.222	3.566	0.023	2.123	0.240	3.191	0.037
Random Intercept								
Variance: individual effect	$\widehat{\psi}^{(2)} =$ 2.15(1.00)							
Variance : Household effect	$\widehat{\psi}^{(3)} =$ 2.76 (0.96)							
Intra-class correlation:								
Individual-level	$\rho_{(iid)}=$ 0. 60							
Household-level	$\rho_{(hid)}$ 0. 34							
Log likelihood	-2489.77							

$\rho_{(hid)}=\dfrac{\hat{\psi}^3}{\hat{\psi}^2+\hat{\psi}^3+\pi^2/3}$, $\rho_{(iid)}=\dfrac{\hat{\psi}^2+\hat{\psi}^3}{\hat{\psi}^2+\hat{\psi}^3+\pi^2/3}$

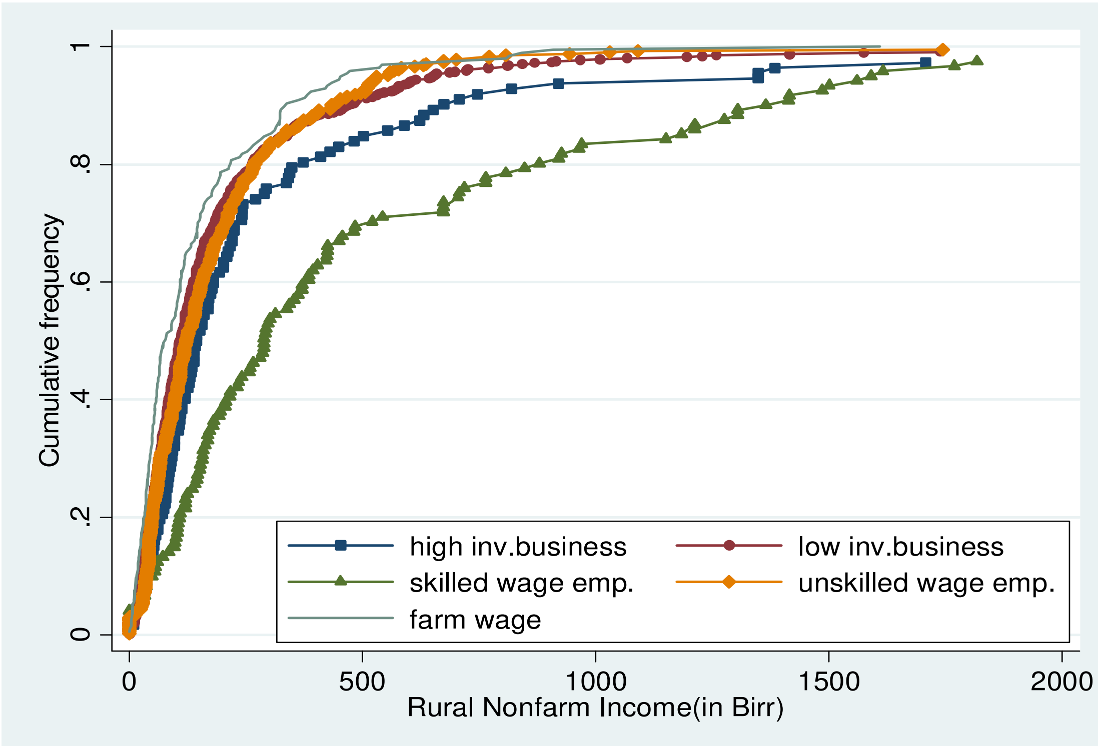

Figure 1 Comparison of income from off-farm activities

Appendix

Estimation procedure

The Stata routine used to estimate our model, **gllamm**, implements maximum likelihood estimation and empirical Bayes prediction for many kinds of generalized linear mixed models with latent variables (Rabe-Hesketh et al., 2002, Rabe-Hesketh et al., 2004). The marginal log-likelihood in a model like ours can be obtained using numerical integration by Gauss Hermite quadrature or adaptive quadrature. Gauss-Hermite quadrature approximates the integral by a specified number of discrete points. Adaptive quadrature is a Bayesian method that extends Gauss Hermite quadrature by making use of the posterior distribution of the unobserved heterogeneity.

The numerical integration and numerical derivation can be very slow when there are many latent variables in the model, many quadrature or free mass-points, many parameters to be estimated and many observations. Roughly, execution time is proportional to the number of observations and the square of the number of parameters. Performance of adaptive quadrature is much better than ordinary quadrature, particularly for large cluster sizes and large intra-class correlations. Furthermore, adaptive quadrature usually requires fewer quadrature points than ordinary quadrature to obtain the same precision (gllamm manual).

Estimation time

Our model has a fairly large number of observations (about 2500) and more than 20 explanatory variables, including the year dummies. It is a three level model with unobserved heterogeneity at individual and household levels. The estimation can take weeks to converge. Before we estimate the full model, we started out with simple models with fewer basic covariates and fewer quadrature points to see how the efficiency as well as the computational time changes with a more complete specification (see Table A.3). In comparing the coefficients and the likelihood between the estimates, we see that the estimates based on the Gauss Hermite quadrature with 7 quadrature points and 10 quadrature points are close. The results from estimation with 4 quadrature points are somewhat different but not very far off. In all the three cases, the sign, relative magnitude and the statistical significance level of the coefficients are the same. Adaptive quadratures are generally considered to have higher accuracy. We also estimated the same model using adaptive quadrature. We estimated the adaptive quadrature using 7 quadrature points. The estimation took 30 hours to converge, more than seven times the time it takes the ordinary 4 quadrature to solve and double that of ordinary quadrature with 7 quadrature points. However the efficiency gain was not as great as the computational cost.

We estimate our full model with 25 explanatory variables using Gauss Hermite quadrature with 7 quadrature points. We control for heterogeneity both at an individual and household level. The estimation took nine days to converge.

Table A1: Comparison of random intercept models estimated using Gauss-Hermite quadrature and Adaptive quadrature

	Gauss Hermite Quadrature						Adaptive Quadrature			
Quad. Points	4		7		10		7		10	
Time (hours: minutes)	04:36		17:21		31:05		29:47		43:15	
Loglikelihood	-2915.193		-2915.45		-2915.324		-2915.34		-2915.34	
	Coefficient	Std.D	Coefficient	Std.D	Coefficient	Std.	Coefficient	Std.D	Coefficient	Std.D
Skilled wage employment										
Gender (=1 female, 0 otherwise)	-0.556	0.556	-0.595	0.550	-0.599	0.552	-0.599	0.552	-0.597	0.552
Age of individual	0.026	0.012	0.023	0.012	0.023	0.012	0.023	0.012	0.023	0.012
Individual is household head	-0.353	0.395	-0.292	0.387	-0.300	0.389	-0.301	0.388	-0.301	0.389
Land holdings per capita	0.417	0.349	0.396	0.351	0.400	0.354	0.401	0.353	0.401	0.353
Household size	0.084	0.050	0.092	0.051	0.094	0.051	0.094	0.051	0.094	0.051
Distance to town	0.041	0.025	0.042	0.025	0.041	0.025	0.041	0.025	0.041	0.025
constant	-1.002	0.628	-1.076	0.614	-1.058	0.618	-1.060	0.617	-1.062	0.617
Unskilled wage employment										
Gender (=1 female, 0 otherwise)	1.850	0.365	1.810	0.357	1.807	0.359	1.806	0.359	1.808	0.359
Age of individual	0.014	0.011	0.011	0.010	0.011	0.010	0.012	0.010	0.012	0.010
Individual is household head	-0.182	0.342	-0.120	0.333	-0.128	0.335	-0.128	0.334	-0.128	0.335
Land holdings per capita	-0.938	0.344	-0.957	0.346	-0.953	0.349	-0.952	0.348	-0.952	0.348
Household size	0.012	0.045	0.021	0.045	0.022	0.046	0.022	0.046	0.022	0.046
Distance to town	0.102	0.022	0.103	0.023	0.102	0.022	0.102	0.022	0.102	0.022
constant	0.553	0.559	0.480	0.544	0.497	0.547	0.495	0.546	0.493	0.546
High investment Business										
Gender (=1 female, 0 otherwise)	0.076	0.492	0.036	0.486	0.032	0.488	0.032	0.487	0.034	0.488
Age of individual	0.004	0.013	0.002	0.012	0.002	0.012	0.002	0.012	0.002	0.012
Individual is household head	0.287	0.400	0.347	0.392	0.339	0.393	0.339	0.393	0.339	0.393
Land holdings per capita	-0.060	0.388	-0.081	0.390	-0.077	0.392	-0.076	0.392	-0.076	0.392
Household size	0.110	0.050	0.119	0.050	0.120	0.050	0.120	0.050	0.120	0.050
Distance to town	0.023	0.025	0.024	0.025	0.023	0.025	0.023	0.025	0.023	0.025
constant	-0.503	0.623	-0.577	0.609	-0.560	0.613	-0.562	0.611	-0.563	0.611
Low investment Business										
Gender (=1 female, 0 otherwise)	2.247	0.359	2.208	0.350	2.204	0.353	2.204	0.352	2.206	0.353
Age of individual	0.019	0.011	0.016	0.010	0.017	0.010	0.017	0.010	0.017	0.010
Individual is household head	-0.420	0.335	-0.358	0.326	-0.366	0.327	-0.367	0.327	-0.367	0.327
Land holdings per capita	0.441	0.303	0.421	0.306	0.425	0.308	0.426	0.308	0.426	0.308
Household size	0.073	0.044	0.082	0.044	0.083	0.044	0.083	0.044	0.083	0.044
Distance to town	0.074	0.022	0.075	0.022	0.075	0.022	0.074	0.022	0.075	0.022
constant	0.519	0.548	0.446	0.532	0.463	0.536	0.461	0.535	0.459	0.535

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