Reconsidering Post Green Revolution Food Choices:
New Processing Technologies and Food Security in India

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Abstract

Though the Green Revolution has played a large role in producing food for increasing populations, the mass production of calories has come with costs. For example, varieties of finger millet (*Eleusine coracana*, known in India as *ragi*), which have largely been replaced during the Green Revolution, are generally more nutritious than high yielding varieties of cereals such as rice, maize, and wheat (National Research Council, 1996). Before being consumed, ragi must be ground into flour, and the drudgery associated with the preparation of this grain for consumption could be prohibiting ragi production amongst subsistence farmers (Finnis, 2009). To help promote the consumption of ragi flour, scholars have advocated the introduction of innovations in processing ragi for small and large-scale entrepreneurs (e.g., Singh and Raghuvanshi 2012). Recently, small-scale flourmills have been introduced into rural villages by the M.S. Swaminathan Research Foundation with the goal of reversing the decline in local ragi consumption and improving food security amongst households in the community that are disadvantaged and have lower levels of wealth. The establishment of these mills was facilitated by entrepreneurial Self-Help Groups (SHGs). This intervention provides us with an opportunity to investigate the introduction of a new technology, facilitated by SHGs. The objective of our research is to investigate the determinants that drive households' use of ragi processing technology. We investigate these determinants using a unique primary dataset, collected from 575 households in rural Tamil Nadu in 2012. Spatial (GIS) techniques were used extensively in our sampling plan and analysis. We employ a two-stage technology adoption framework as a basis for analyzing two key decisions made by the household regarding the production of ragi flour: 1) whether or not to adopt the processing technology (the adoption equation), and – conditional upon adoption – 2) how much ragi flour to produce (the intensity equation). This approach allows us to address a number of key policy questions: Is ragi flour a "poor-person's food" (i.e. an inferior good, as suggested by social stigma), or is it a normal good? How do demographic factors affect the adoption and intensity of use of this technology? What are the effects of the prices of ragi grain, ragi flour, and wheat flour on the adoption and intensity decisions? How do the travel costs of accessing these mills affect household's decision to adopt the milling services? In analyzing these questions, we pay attention to potential selection biases in adoption caused by unobserved variables. We explore whether the effects of these unobserved variables are consistent with increasing or decreasing welfare. We find that the mills are systematically being placed in close proximity to wealthier households, despite evidence that disadvantaged households have a higher propensity to adopt this technology.

Keywords: Technology Adoption, Selection Effects, Household Welfare, Rural India, Finger Millet, Ragi, *Eleusine coracana*, Flour Production

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The remarkable possibility that millets offer for an internal input based farming, free from chemicals and corporates make them the new age answer to a new age crisis. ... the rejuvenation of millet farming, continuously undermined by the Green Revolution protagonists, is the only way we can ensure our food, fodder, health, nutrition, livelihood and ecological securities.

- Sateesh P.V, 2008. p. III. Deccan Development Society

1. Introduction

Though the Green Revolution has played a large role in producing food for increasing populations, the mass production of calories has come with costs. For example, varieties of finger millet (*Eleusine coracana*, known in India as *ragi*), which have largely been replaced during the Green Revolution, are generally more nutritious than high yielding varieties of cereals such as rice, maize, and wheat (National Research Council (NRC), 1996). Ragi in particular has a high protein and mineral content. Although some rice varieties contain more protein by weight, the proteins found in ragi contain a high amount of the essential amino acid methionine. Because methionine is generally lacking in grain based diets, ragi might be considered a nutritional “super food” for much of the developing world (NRC, 1996).

As with many traditional grains, ragi is also well ad apted to local climatic conditions and is genetically diverse. Further, relative to modern crops, traditional grains require fewer chemical inputs, are more tolerant to environmental shocks, and are predicted to be more robust to climate change (Altieri & Koohafkan, 2008; Seetharam *et al*, 1989). Accordingly, the promotion of traditional grains, such as ragi, has been identified as an intervention that could improve the food security of households in India and in other places such as Africa (NRC, 1996). Traditionally, ragi has been a popular staple amongst the working class in rural India because of its ability to provide sustenance for long periods of manual labour. Ragi grain can also be stored for a long time before consuming; some reports indicate that it can be stored upwards of 50 years (Food and Agricultural Organization (FAO), n.d.). As a result, stores of ragi grain can provide insurance against future food shortages.

Despite its potential benefits, the production and consumption of ragi has declined sharply in India. The consumption of ragi has declined in favour of subsidized green revolution grains, such as rice and wheat (NRC, 1996; Rao et al, 2003). These subsidies have driven down the prices for ragi, and as a result the production of ragi has been crowded out by the presence of more profitable cash crops such as cassava. Other factors which may contribute to this decline include the cultural stigma associated with this grain; historical preferences for ragi amongst the poor has caused it to become culturally stigmatized as a “poor person’s crop” and a “famine food” (NRC, 1996). Moreover, the drudgery associated with ragi cultivation and the preparation of this grain for consumption could be prohibiting ragi production amongst subsistence farmers (Finnis, 2009). Before being consumed, ragi must be ground into flour because it has a tough seed coat surrounding the grain. The traditional method of producing ragi flour is to manually grind the grain using a stone grinder. This method is both time and energy intensive, requiring approximately one hour between two people to produce a kilogram of flour (M.S. Swaminathan Research Foundation, 2012; field observations). Because producing flour is culturally defined as a female task, the costs associated with manually preparing this grain have historically been borne by female members of the household.

To help promote the consumption of ragi flour, scholars have advocated the introduction of innovations in processing ragi for small and large-scale entrepreneurs (e.g., Singh and Raghuvanshi 2012). These innovations have the potential to encourage ragi consumption by reducing the labour costs associated with the traditional methods of flour production. However, structural deficiencies in markets typically characterize economies where ragi is argued to provide the largest benefits. These deficiencies include the inability of entrepreneurs to access credit, and a lack of information regarding local demand for milling services. As a result, few incentives exist for entrepreneurs to develop these technologies in areas where they have the greatest potential to address deficiencies in food security.

Recently, this technology has been introduced into rural villages by the M.S. Swaminathan Research Foundation (MSSRF) with the goal of reversing the decline in local ragi consumption and improving food security amongst households in the community that are disadvantaged and have lower levels of wealth. The establishment of the flourmills was initiated by local village members. Entrepreneurial Self-Help Groups (SHGs) were established by village members to start-up and manage the operations of the flourmills. These groups each consisted of a minimum of 10-12 members. This number of people was needed to fulfill minimum requirements to open an account with a local bank in order to pay for the electricity to run the mill. The SHGs were also required to identify a piece of land already owned by a SHG member, or acquire a new piece of land, upon which to place the mill. The MSSRF purchased the milling unit and all necessary construction materials, while the SHG built the structure to house the mill and covered the costs of running and maintaining the mill. The members of the SHG collectively own and operate the milling centre as a private business.

This intervention provides us with an opportunity to investigate the introduction of a new technology, facilitated by SHGs. SHGs may be more effective at managing small business operations than larger centralized organizations, such as governments or non-profit organizations. In many centralized management systems there is a high potential for moral hazard problems that may arise due to the information asymmetries between the business operators and the organization that establishes the business. SHGs may be able to avoid such problems because their members likely have greater information to assess the trustworthiness of other members, and because their monitoring costs are likely lower. On the other hand, larger organizations may be better positioned to establish a capital-intensive enterprise such as a flourmill because they are likely to have greater access to credit. Although SHGs are often formed as a means for members to overcome personal credit constraints, it may be difficult for many SHGs to raise sufficient capital to purchase a flourmill. Using SHGs to facilitate the introduction of this technology thus presents an opportunity for development organizations to utilize the strengths of both management approaches; the organization, in this case the MSSRF, is able to overcome credit constraints of establishing the mill, while the SHG is able to avoid potential problems associated with management and supervision of the mill operations.

In response to the development of a local supply of ragi mills, local demand for milling services has emerged. However, there is little empirical evidence regarding how technological advances in processing have been received in rural communities. Basic questions for informing policymakers regarding the introduction of processing centres remain unanswered. We address this knowledge gap by investigating the outcomes of this intervention.

The objective of our research is to investigate the determinants that drive households' use of ragi processing technology. We begin our research with an exploratory analysis of how probabilities of adoption vary with household wealth and costs of access to the mill. We estimate probability functions for households' adoption of milling services for the production of ragi flour, using local polynomial regressions. We then use a two-stage technology adoption framework as a basis for analyzing two key decisions made by the household regarding the production of ragi flour: 1) whether or not to adopt the processing technology (the adoption equation), and – conditional upon adoption – 2) how much ragi flour to produce (the intensity equation). We estimate these two stages simultaneously using maximum likelihood methods. This approach allows us to address a number of key policy questions: Is ragi flour a "poor-person's food" (i.e. an inferior good, as suggested by social stigma), the consumption of which declines with increasing wealth; or is ragi flour a normal good? How do demographic factors affect the adoption and intensity of use of this technology? What are the effects of the prices of ragi grain, ragi flour, and wheat flour on the adoption and intensity decisions? How do the travel costs of accessing these mills affect household's decision to adopt the milling services? In analyzing these questions, we pay attention to potential selection biases in adoption. For example, the innovativeness and productivity of households could drive self-selected groups to disproportionately adopt the processing technology. These unobservable variables may in turn be correlated with ragi flour consumption levels that can bias the intensity equation estimates. We explore whether the effects of these unobserved variables are consistent with increasing or decreasing welfare. Consumption is often used as a measure of welfare (Deaton, et al., 2002), and marginal changes in ragi flour consumption may reflect marginal changes in household welfare. The self-selection patterns of ragi flour consumption may therefore be indicative of unobserved levels of household welfare. Accordingly, we pay special attention to the patterns of self-selection in our analysis, and to the potential welfare implications of these patterns regarding the households that adopt this technology.

In the next section, we present the empirical model used in our analysis. In the third section we discuss econometric considerations with respect to estimating this model, and in the fourth section we give background information on our study site and outline our data collection methods. In the fifth section we present the results from our analysis, and in the sixth section we present conclusions.

2. The Empirical Model

For each household *i*, we model the use of this technology as a two-stage adoption decision process: the binary decision to adopt this technology for the purpose of producing ragi flour (A_i), and the continuous choice of intensity of use (Q_i). We define the intensity of mill use as the natural logarithm of the quantity of ragi flour (kg) produced using this technology in one month per capita (i.e. $Q_i = \ln\left(\frac{kg.\ of\ ragi\ flour\ produced\ in\ one\ month}{adult\ equivalent\ household\ size}\right)$).[1] We consider the following econometric specification:

$$A_i^* = X_i\alpha + e_i \qquad (1)$$

[1] Adult equivalent household size: See Appendix

$$A_i = \begin{cases} 1 & if\ A_i^* > 0 \\ 0 & otherwise \end{cases}$$

(2) $$Q_i^* = Z_i\beta + u_i$$

$$Q_i = \begin{cases} Q_i^* if\ A_i = 1 \\ 0\ otherwise \end{cases}$$

where the outcome variables A_i^* and Q_i^* denote the latent propensity to adopt and use the technology, respectively. A_i is equal to one if household *i* chooses to adopt the technology, and zero if otherwise. Its value is determined by whether the latent utility gain from using the technology (A_i^*) is positive. Q_i is equal to zero if A_i is equal to zero, and equal to Q_i^* if A_i is equal to one. The row vectors X_i and Z_i denote causal factors influencing technology use and intensity, respectively. These vectors contain household specific income, price, and demographic variables that are listed in Table 1. The construction of several of these variables is outlined in the appendix.

For the most part, we expect $X_i$and Z_i to contain the same variables, as many factors that affect adoption and intensity are the same. Table 1 shows that there are two variables: *Cultivates Ragi* and *Travel Cost Index*, which we expect to affect adoption but not intensity. Because of the need to grind ragi before it is consumed, we expect a household that *Cultivates Ragi* to have a greater propensity to adopt this technology. We observe that only 2.7% of randomly sampled households sell ragi grain. Because this grain cannot be eaten whole, households who cultivate ragi tend to grind it into flour. Although households do have the option of grinding this grain at home using a stone grinder, we find that only 2% of randomly sampled households grind this grain at home, while the majority of households produce ragi flour by bringing their grain to a flourmill. We do not, however, expect the decision to cultivate ragi to affect the intensity of use. Because ragi grain can be stored practically indefinitely (up to 50 years or more) without turning rancid or rotting, households that cultivate greater quantities of ragi are not compelled to process greater quantities of ragi to prevent spoilage. In contrast, ragi flour has a relatively short shelf-life of a few weeks. Therefore, households are likely to grind only enough flour for short-term consumption. This assertion is supported by the fact that we find a high degree of variation in the amount of ragi cultivated, but a low degree of variation in the amount of ragi flour produced. The mean amount of ragi cultivated is 51 kg per household per year, with a standard deviation of 41 kg and a coefficient of variation of 0.80. In contrast, the mean amount of ragi flour produced per month is 4.7 kg per household with a standard deviation of 2 kg and a coefficient of variation of 0.43. This difference in relative variation suggests that the amount of ragi cultivated by a household annually is independent from monthly consumption decisions that drive ragi flour production.[2] The relative variations between the amount of ragi cultivated and amount of ragi flour produced also suggests that the decision to cultivate ragi is likely to have little influence on the amount of ragi flour produced.

Travel Cost Index is a variable that approximates the cost for a member of household *i* to travel to the nearest flourmill. This variable is measured by the Euclidean distance between the household and the nearest mill, weighted by the difference in elevation between the household

[2] Furthermore, in an exploratory analysis that is not presented in this paper, we found that after controlling for Z_i we did not observe a significant relationship between intensity and the variable *Cultivates Ragi*.

and the mill (see appendix). We predict that travel costs will decrease the probability of adoption, because they effectively increase the costs of accessing this technology. We argue that travel costs – which are most commonly in the form of walking to and from the mill – affect only the fixed costs of accessing the technology and therefore will influence the decision to adopt the technology and not the intensity decision. One could argue that because the household member who accesses these mills on foot must carry the weight of the ragi, an increase in the quantity of flour produced will lead to increased travel costs associated with the effort of carrying more weight to and from the mill; households that must travel greater distances to the mills may therefore choose to mill smaller amounts of ragi flour to reduce the costs of carrying a heavy load. However, we do not believe that the cost of carrying ragi significantly affects the amount of ragi taken to the mill. As mentioned above, the average amount taken to the mill is 4.7kg (± 2.0), a quantity that is likely dictated in part by the short shelf-life of ragi flour. Based on field observations, this weight seems small relative to weights of other items that are carried long distances, and we therefore do not expect travel costs to significantly affect the intensity decision. Moreover, if the weight of carrying this quantity of flour was a limiting factor, we would expect to see some households making multiple trips per month. If households are making multiple trips, travel costs would therefore represent a variable cost and would need to be included in the intensity equation. However, there are no observations of multiple trips being taken to the mill within a month, so we therefore treat the *Travel Cost Index* as a fixed cost of accessing this technology.[3]

Table 1 shows that we expect the remaining explanatory variables to affect both adoption and intensity. We use *Wealth Index*[4] to approximate household income because total household income is often difficult to measure accurately for subsistence households and because measures of wealth have been shown to be positively correlated with long term income levels (Sonalde *et al.*, 2008; page 18). We have no information to suggest how this variable might affect the rate of adoption, and we seek to understand the role of wealth in adoption. We are also unable to make a prediction with respect to the effect of household wealth on the intensity of use decision, because we do not know whether ragi flour is a normal good. The nutritional benefits of ragi flour suggest that it may be a normal good, of which we would expect to see wealthier households consume more. However the cultural stigma surrounding this grain suggests that it may be an inferior good. If ragi is a normal good, we would expect a positive coefficient on *Wealth Index* in the intensity of use equation. Conversely, if ragi flour is an inferior good, we would expect a negative coefficient.

Characteristics of the household head, that is, whether the head is a *Female Head*, *Literate Head*, or a *Widowed Head*, are likely to affect the adoption and intensity of use decisions. Because women are often responsible for millet cultivation and post-harvest operations (FAO, 2013), and because this technology has the potential to reduce the amount of labour faced by women, we expect households with a *Female Head* will have a higher propensity to adopt this technology and will use this technology at a higher level of intensity than male-headed households. We expect heads that are literate to have a greater awareness of the nutritional benefits of ragi. As a result, we expect that households with a *Literate Head* will also have a higher probability of adoption and will use this technology at a greater intensity. We also

[3] In an additional exploratory analysis that is not presented in this paper, we found that after controlling for Z_i we did not observe a significant relationship between intensity and the *Travel Cost Index.*

[4] See Appendix regarding the construction of this variable

expect that the effect of literacy on adoption and intensity will differ between male and female headed households. We account for these differences by including the interaction term *Female Head × Literate Head* in our regression. Because we expect the variables *Female Head* and *Literate Head* to both increase the probability of adoption and intensity of use, we expect the interaction term *Female Head × Literate Head* to increase the probability of adoption and intensity of use. Households with a *Widowed Head* have been shown to differ significantly from other households with respect to household welfare (van de Walle, 2013) and their probability of adopting certain technologies (Barungi & Maonga, 2011). Although we expect the variable *Widowed Head* could affect the adoption and intensity of use decisions, we do not have expectations with respect to the effects of this variable on either decision.

We also expect that the gender composition of the household will affect the household's adoption and intensity of use decisions. We expect that *Male Dominant Households*, which have a greater number of adult males than females, will have a lower probability of adopting this technology and will use this technology at a lower intensity. Because cultural norms dictate that females are responsible for cultivating and processing ragi, and because imperfect labour markets limit the ability of households to hire additional labour, the economic decisions of households with relatively few females will be constrained by low levels of available "female labour" in comparison to households with many females. This labour constraint may therefore reduce the intensity of use.

The number and age composition of children in the household may also influence the adoption and intensity decisions. The *Proportion of Household Members that are Children* could influence ragi flour production because children tend contribute less to household production than adults. This variable may therefore be inversely related to household productivity per person. Additionally, we expect that the *Number of Children Age 0-6*, *Number of Children Age 7-12*, and the *Number of Children Age 13-17* will all affect the adoption and intensity of use decisions. The preferences for ragi flour may vary with age, and could result in effects that differ by age category. However, with no information regarding the role of children in ragi flour production, we have no expectations with respect to whether the proportion of children in the household or the number of children of different ages will increase or decrease the probability of adoption or the intensity of use.

Because older household members may have preferences for ragi flour that differ from that of other household members, we expect that a *Senior Male in the Household* or a *Senior Female in the Household* may have an effect on the household's probability of adoption and intensity of use. However we have no expectation regarding the effects of these variables.

The market variable, *Buys Ragi Flour* is also predicted to be a determinant of adoption and intensity of use decisions. Because purchased ragi flour is likely to be a close or a perfect substitute for ragi flour produced using the milling technology in terms of taste and other qualities, households that purchase ragi flour will need to produce less ragi flour using the mills in order to attain a given level of ragi flour consumption. Households that obtain all of their ragi flour from the market will not need to adopt this technology. Thus we expect that a household that *Buys Ragi Flour* will have a lower probability of adopting this technology and will use this technology at a lower intensity.

We expect the *Price of Ragi Flour*, *Price of Ragi Grain*, and the *Price of Wheat Flour* to affect the adoption and intensity of use decisions. These prices are expressed as the price per kilogram that is experienced by household i. Variability in the *Price of Ragi Flour* and the *Price of Ragi Grain* that is experienced by different households is likely due to differences in the remoteness of households and their ability to access central markets, as well as the ability of households to receive quantity discounts by purchasing larger quantities. Because of the substitutability of purchased ragi flour for ragi flour produced with the milling technology, we expect that households that experience a higher *Price of Ragi Flour* will be more likely to adopt this technology and will use this technology at a higher intensity. Because ragi grain is an input for the production of ragi flour, we expect that households that experience a higher *Price of Ragi Grain* will have a lower probability of adopting this technology and will use this technology at a lower intensity. The main source of variability of the *Price of Wheat Flour* is likely due to the different legislated prices that are available through the Public Distribution Service to low-income households and people that are otherwise identified as being disadvantaged such as being disabled, widowed, or terminally ill (Tamil Nadu Civil Supplies Corporation, n.d.). We expect that wheat flour is a substitute for ragi flour, and we therefore expect that households that experience a higher *Price of Wheat Flour* will be more likely to adopt this technology and will use this technology at a higher intensity.

3. Econometric Considerations

In modeling our adoption problem, we attempt to account for unobserved heterogeneity. The two-stage econometric model yields estimates of the relationship between observed household attributes (such as wealth and education of the head) and adoption behaviour. However, participation in the mills is also likely to be driven by unobservable attributes, which can cause some groups to disproportionately self-select into the group of households that adopt the processing technology. These unobservables may in turn be correlated with ragi flour consumption levels, which can bias the intensity equation estimates. Thus the presence of selection bias implies that $\rho = Cov(e_i, u_i) \neq 0$. We therefore correct for selection bias using Heckman's correction. Heckman (1976) shows that the effects of unobserved characteristics on self-selection can be captured by the inverse Mill's ratio, denoted by $\lambda_i = \frac{\phi(H_i)}{1-\Phi(H_i)} = \frac{\phi(H_i)}{\Phi(-H_i)}$, where ϕ and Φ are the density and distribution functions for a standard normal variable, respectively, and $H_i = -\frac{X_i\hat{\alpha}}{(\sigma)^{\frac{1}{2}}}$ where σ is the standard deviation of u_i. Heckman demonstrates that including the correction term λ_i as a regressor of Q_i (equation 2) will correct for potential selection bias. Thus, to account for selection bias, we rewrite the intensity equation as:

$$Q_i^* = Z_i\beta + \lambda_i\beta_\lambda + u_i \tag{3}$$

In addition to controlling for potential selection bias, the inclusion of λ_i as a regressor in the intensity equation allows us to test for the presence of selection bias, via a t-test of the correction term coefficient, $\beta_\lambda = \rho\sigma$. If β_λ is not significant, this implies that $\rho = 0$, and therefore that selection bias does not exist. If the coefficient is positive and significant, positive selection bias exists; this means that some unobserved characteristic that increases the propensity of households to self-select into the group of adopters is also increasing average levels of intensity, above what would be expected if the decision to adopt this technology was random. Likewise, if β_λ is negative and significant, negative selection bias exists, indicating that some unobserved characteristic that increases the propensity of households to self-select into the group of adopters is decreasing the average levels of intensity, below what would be expected if the adoption decision was random.

We employ this correction parameter for paying special attention to the patterns of self-selection. One of the challenges we face in addressing whether households with higher or lower levels of welfare have a higher probability of adopting this technology is the absence of detailed data with respect to the multitude of factors that contribute to household welfare. This problem could be magnified by the potentially large role played by unobservable factors in household economic behavior. Following the work of Borjas (1987), Borjas and Bronners (1989), and Kawaguchi (2005), we attempt to profile the types of households that are self-selecting into the group of adopters. We look for evidence of unobservable aspects of welfare that may be driving this adoption decision. As we demonstrate in the results section of this paper, the patterns of self-selection observed in the data can be useful for identifying whether households with higher or lower levels of welfare – based on unobserved characteristics – have a higher propensity to adopt this technology.

One problem that can arise in the estimation of a two-stage Heckman selection model is collinearity between λ_i and Z_i, which can reduce the efficiency of model estimates (Little & Rubin, 1987, p. 230). This collinearity can be reduced by including identifying variables (also known as exclusion restrictions) in the model. Identifying variables are variables that are included in X_i but absent in Z_i: variables expected to affect the decision to adopt, but not the intensity decision. Failure to include identifying variables can result in a high degree of multicollinearity, due to the high correlation between λ_i and Z_i (Leung & Yu, 1996). Bushway, Johnson, and Slocum (2007) argue that in the absence of technical grounds for identifying exclusion restrictions, the choice of which variables to exclude from the intensity decision must be made on substantive grounds. In the previous section, we argued that the variables *Cultivates Ragi* and *Travel Cost Index* would have an effect on the adoption decision, but not the intensity of use decision. These two variables therefore serve as our identifying variables and may reduce the potential collinearity between λ_i and Z_i.

4. Study Site and Data Collection

4.1 Study Site

Our study is based in the Kolli Hills region of Tamil Nadu, India. Kolli Hills (*Kolli Malai*, in Tamil) is a small mountain range located on the southern end of the Eastern Ghats, and is located in central Tamil Nadu in the district of Namakkal. 98% of the people living in this rural area belong to the scheduled tribal communities (Raghu, et al., 2013), which are recognised in India as being a marginalized social group (Chatterjee & Sheoran, 2007). Most households earn their primary income from agriculture and livestock and the main mode of transportation for most residents is by foot (Raghu, et al., 2013).

4.2 Data Collection

We conducted two preliminary surveys to help inform our study design and the creation of our main survey instrument. These surveys were translated and implemented by MSSRF staff. One survey targeted the operators and owners of the mills in our study site, and the other targeted customers of those mills that came in a single day. The goal of both surveys was to obtain rough estimates on: 1) the number of customers that came to the mills each day; 2) the distances and modes of travel for the average mill customer; 3) the frequency of mill visits by the customers; and 4) the average amount of grain brought to the mills.

On the day that we conducted our preliminary survey, a total of 25 customers came to the three mills. We found that the majority of customers walked to the mill, and that the average distance walked to the mill was 1.2 km; the greatest distance walked was 4 km. The preliminary survey indicated that customers came to the mills approximately once per month and that the average amount of grain brought by customers was 5 kg.

We collected our primary data with household surveys. The survey was translated into Tamil by members of the MSSRF who were fluent in both English and Tamil. The data was collected from March until May, 2012. Because the literacy of the participants was a concern, the surveys were completed as an interview between household participants and trained enumerators. Four local enumerators were hired because of their fluency in Tamil and their familiarity with the study area. Training of the enumerators was carried out by the primary author with the assistance of a translator fluent in both English and Tamil. Pre-tests were conducted to ensure that the enumerators were comfortable and able to administer the survey, and to ensure that the questions were clear. The pre-tests were conducted on households who were not included in the final survey sample.

We employed a mixed sampling plan for the collection of our main survey instrument, which included a random sample and a sample composed entirely of adopters. The random sample was conducted to understand the true proportion of flour production strategies employed in our study site. Based on the frequency of customers who came to the mills during our preliminary survey, the average distances traveled to the mills, and on our the estimates of local population density (made by identifying individual households using satellite imagery from Google Earth, 2012), we concluded that a random sample would not provide sufficient observations of adoption for our analysis. The sample of adopters was therefore included as a means to augment the observations of adoption in the random sample. We correct for this mixed sample in the estimation of our model using sampling weights, as outlined by Greene (2007).

We collected our sample of adopters from customers who visited either of two mill sites. The sample of adopters was collected by having an enumerator posted at each mill in our study site every day during the mill's hours of operation, for the entire data collection period of six weeks. The enumerators collected the names and addresses of all customers who came to the mills during the collection period and were willing to participate in a follow-up survey conducted at their home. None of the customers who came to the mills during the collection of our sample of adopters refused to participate. In addition to completing the survey, enumerators also collected the GPS location and elevation of the homes of participating households. Observations from 315 households who milled ragi were collected; however five observations were excluded from our analysis for being incomplete. The sample of adopters was collected first in order to verify the maximum distance traveled by customers on foot; using the GPS data, we found this distance to be approximately 4.5 km. This distance was used to inform our random sampling plan.

Because we expected that the travel costs from the household to the mill would be a significant factor in the decision to adopt this technology, the relative location of the households to the mill was a key consideration in the design of our random sampling plan. We wanted to ensure that our random sampling plan would adequately represent the flour production decisions of households living near and far from the mills. Given that the maximum distance travelled on foot to the mill in the sample of adopters was 4.5 km, we decided to draw our random sample from a 5.5 km radius around each mill. We thought that by extending our sampling radius beyond the maximum distance observed in the sample of adopters, we would have a greater chance of observing the full range of variation in the adoption decisions as they vary with respect to distance. In the collection of our random sample, we found that several households visited mills other than the two from which we collected our random sample; we identified seven additional mills that were visited by households in our random sample.

The GIS software, Google Earth (2012), was used to plot the 5.5 km sampling radius around the two mills from which we collected our sample of adopters. This was cross referenced with a hard-copy map of block districts[5] in Kolli Hills. Complete household lists were obtained from each Block District Office that fell within these radii. The total number of households in this area was 4,243. These lists were compiled and households were randomly drawn from this list for possible inclusion in our sample. Enumerators contacted these households, and collected GPS and survey data from those households. Of the 275 households that were randomly selected 262 households were willing to participate. However, six of these observations were excluded from our analysis for being incomplete. Because our refusal rate was low (4.7%) we are confident that our sample is representative of the population.

5. Results

5.1 Summary of Data

Table 2 gives the summary statistics of the variables used in our analysis from the random sample. We find that more households purchase ragi flour than produce it using the mills; 24% of our sample adopts this technology for the production of ragi flour while 37% purchase ragi flour. The average amount of ragi flour produced is 2 kg per person per month (I_i= 0.56). We also find that 10% of the population cultivated ragi in the year previous to participating in our survey, while 27% of households bought ragi grain in the month previous to our study.[6] This suggests that a majority of the adopters of this technology are purchasing ragi grain, not growing it themselves. The average value for the *Travel Cost Index* is 0.17; the average distance between the household and the mill is 1.9 km, while the average difference in elevation between the household and the mill is 66 m. We find that 11% of household heads are female and that 66% of household heads are literate. The literacy rate amongst female heads is lower than male heads; 4% of household heads are both female and literate, meaning that only 36% of female heads are literate. We find that 22% of the households in our sample have more

[5] Block Districts are local government subdivisions in Tamil Nadu, which are composed of several villages.

[6] The proportion of households that bought ragi grain is not presented in Table 2. Because ragi grain cannot be eaten without being ground into flour, the decision to buy ragi grain is likely confounded with the decision to produce ragi flour. Consequently, we chose to not include the decision to buy ragi grain in our analysis.

adult men than women, indicating that a majority of the households in our sample either have equal numbers of adult men and women or are dominated by females. We find that households tend to have more adults than children, with the average proportion of children in the household at 37%. There are few households with members over the age of 65; 6% of households have a senior male member and 7% of households have a senior female member.

5.2 Exploratory Analysis of Adoption

We perform an exploratory analysis with a series of three non-parametric regressions. We begin by exploring the relationship between the *Wealth Index* and the decision to adopt the milling technology for the production of ragi flour (A_i). Figure 1 shows a clear upward trend; as the household's *Wealth Index* increases, the probability of adoption increases. We also explore the relationship between the *Travel Cost Index* and the decision to adopt the mill. Figure 2 shows that there is a negative and significant correlation between the *Travel Cost Index* and the probability of adopting this technology. Given that we find significant relationships between adoption and the household's *Wealth Index*, and adoption and the *Travel Cost Index*, we also investigated the relationship between the *Wealth Index* and the *Travel Cost Index*. Figure 3 shows that there is a negative and significant correlation between the household's *Wealth Index* and their *Travel Cost Index*, indicating that, on average, the mills are located in closer proximity to wealthier households than less wealthy households.

The positive relationship between the household's *Wealth Index* and adoption suggests that wealthier households are more likely to adopt this technology. The negative relationship between the *Travel Cost Index* and adoption is expected, since transportation costs have been shown elsewhere in the literature to be a deterrent to accessing natural resources (Alavalapati, 1990) and participation in markets (Renkow, Hallstrom, & Karanja, 2004; Key, Sadoulet, & de Janvry, 2000). However, the finding that the mills are placed in close proximity to wealthier households suggests that the location of the mills may contribute to the uptake of this technology amongst wealthier households. Taken together, these results beg the question: why are wealthier households more likely to adopt this technology? Is it because they have a greater inherent propensity to adopt this technology, or is it because the mills happen to be located in close proximity to wealthier households? We revisit this question in our adoption model by examining whether the household's *Wealth Index* increases the probability of adoption, independent of the effects of the *Travel Cost Index*.

5.3 Multivariate Analysis of Adoption and Intensity of Use

We evaluate the effects of household-level characteristics, prices, and travel costs on the adoption and intensity of use decisions. We also control and test for the presence of patterns of self-selection, indicated by the selection term λ_i. We demonstrate how these patterns of self-selection can be used to reveal information about unobservable aspects of household welfare that are associated with a high probability of adoption. The results of this analysis are presented in Table 3.

5.3.1 Adoption and Intensity

Both of our identifying variables, *Cultivates Ragi* and *Travel Cost Index,* are highly significant. This suggests that λ_i is not likely to be collinear with the parameters in the intensity equation. As expected, we find that a household that *Cultivates Ragi* is more likely to adopt this technology. Households who cultivate this grain are 47% more likely to adopt this technology than households who do not. As expected, we also observe a negative and significant correlation between the *Travel Cost Index* and the probability of adopting the technology. Evaluating this coefficient at the mean difference in elevation between the household and the mill of 66 m, we observe that for each additional kilometre that the household is located away from the mill, households are 2.7% less likely to adopt the milling technology. We find that the price of wheat flour decreases the propensity for households to adopt this technology; as the price of wheat flour increases by 1INR/kg, households are 1% less likely to adopt this technology. One possible explanation for this result is that because the price of wheat flour available through the Public Distribution System is based partially on household income, the price effect of wheat flour could be confounded with an income effect.

None of the other variables included in the adoption regression are significant. Most notably, the lack of significance of the coefficient on the *Wealth Index* suggests that wealthier households do not have an inherently higher propensity to adopt this technology, after controlling for other factors. We expected that households who purchased ragi flour would have a lower propensity to adopt this technology. However, we find that households that purchase ragi flour do not differ significantly in their propensity to adopt than households that do not purchase ragi flour.

In our data, we observe that none of the households in our random sample sell the ragi flour that they produce.[7] Thus, we assume that ragi flour production is equivalent to consumption. We observe a positive and significant correlation between intensity of use and our proxy for income, the *Wealth Index*, which suggests that ragi flour is a normal good. For each additional asset that is owned per person in the household, the amount of ragi flour produced increases by 12%.

As expected, we observe positive and significant coefficients for the variables *Female Head* and *Literate Head* in the intensity equation. On average, female headed households produce 83% more ragi flour per person than male headed households. Households with literate heads produce 13% more ragi flour per person than households with illiterate heads. Unexpectedly, we find the coefficient for the interaction term *Female Head* × *Literate Head* to be negative and significant in the intensity equation. Comparing the net effect of the variables *Female Head*, *Literate Head*, and *Female Head* × *Literate Head*, we find that households with literate or illiterate female heads produce more ragi flour than male-headed households. Households headed by literate males produce more ragi flour than households headed by illiterate males, but households headed by literate females produce less ragi flour than households headed by illiterate females. Households with literate females produce: 54% more ragi flour than households with an illiterate male head, 41% more ragi flour than households with a literate male head, but 29% less ragi flour than households headed by an illiterate female. The finding that households headed by females produce more ragi flour than households headed by males, irrespective of literacy, is congruent with our expectations regarding the effect of female headship on the intensity of use. However, the finding that households headed by illiterate females produce more ragi flour than households headed by literate females suggests that our expectation that households with literate heads would have a greater knowledge of the benefits of ragi flour, and would therefore produce a greater quantity of ragi flour, does not hold. Literacy is often correlated with higher levels of income, and these unexpected results may be the result of

[7] However, in our sample of adopters, 2.2% of the households (or 1.09% of households in our total, unweighted sample) sold ragi flour.

effects that are confounded by income. If the literacy of the head is associated with higher levels of household income, then these results may indicate that males tend to view ragi flour as a normal good while females may view ragi flour as an inferior good. The coefficient for the variable *Widowed Head* is negative and significant; households with widowed heads produce 33% less ragi flour per person than households with non-widowed heads.

As expected, we observe a negative and significant coefficient for the variable *Male Headed Household* in the intensity equation. We observe that households dominated by men produce 14% less ragi flour per person than households dominated by females or households with an equal number of adult males and females.

The coefficient for the variable *Proportion of Household Members that are Children* is positive and significant in the intensity equation. A 1% increase in the proportion of household members that are children leads to a 1.35% increase in the production of ragi flour per person. If households with more children tend to have lower levels of productivity per person, as suggested above, then this result may indicate that households with lower levels of productivity tend to produce greater quantities of ragi flour. We find negative and significant coefficients for the variables *Number of Children Age 0-6*, *Number of Children Age 7-12*, and *Number of Children Age 13-17* in the intensity equation. An additional child in the household age 0-6 decreases consumption by 36% per person, an additional child age 7-12 decreases consumption by 33%, and an additional child age 13-17 decreases consumption by 38%. These negative coefficients suggest that children of all ages consume less ragi flour, and that these consumption levels vary with age. The coefficient for the variable *Senior Male in the Household* is positive and significant in the intensity equation, indicating that the presence of a male in the household that is age 65 or older increases consumption by 29% per person. In contrast, we find that the coefficient for the variable *Senior Female in the Household* is insignificant in the intensity equation, suggesting that the presence of a female in the household that is 65 or older does not significantly affect consumption levels of ragi.

The variable *Buys Ragi Flour* is negative and significant in the intensity equation. Households that buy ragi flour from the market tend to produce 26% less ragi flour using the milling technology. As expected, this result suggests that households that purchase ragi flour are substituting it for ragi flour produced from the mill.

All of the price effects that we observe are significant in the intensity equation and match our expectations. As the *Price of Ragi Flour* increases by 1 INR/kg, household production of ragi flour from the mill increases by 2%. As the *Price of Ragi Grain* increases by 1 INR/kg, the household production of ragi flour decreases by 3%. As the *Price of Wheat Flour* increases by 1INR/kg, household production of ragi flour increases by 2%.

5.3.2 Patterns of Self-Selection

As mentioned above, patterns of self-selection observed in the data can contain critical information about economic behaviour. These patterns can give us useful insights with respect to unobserved attributes that are associated with households that self-select into the group of adopters. Our interpretation of these patterns of self-selection is based upon the coefficients that we observe for the *Wealth Index* and λ_i. The positive coefficient on the variable *Wealth Index* suggests that ragi flour is a normal good. By the definition of a normal good, we therefore expect that households with higher levels of income (approximated by the *Wealth Index*) will consume more ragi flour. We also expect that higher consumption levels of ragi flour will be associated with higher levels of household welfare. The selection term λ_i captures the effects of unobserved household characteristics that are associated with a higher probability of adoption. We observe a negative coefficient on λ_i, indicating that some unobserved household characteristic that is associated with a higher probability of adoption is associated with lower levels of ragi flour consumption. Given that ragi flour is a normal good, the negative coefficient implies that this unobserved characteristic could also be associated with lower levels of welfare. These results suggest that disadvantaged households – based on unobserved characteristics – have a higher probability of adopting this technology.

6. Conclusions

In response to our first research question, whether ragi flour was a normal or inferior good, our results indicate that it is a normal good. This result gives us insights into the economic behaviour of households; consumption levels of ragi flour increase as household income increases.

Our second research question asked how demographic factors affect the adoption and intensity of use of this technology. Our results suggest that household demographic characteristics have an insignificant effect on the household's decision to adopt this technology, but that they do have significant effects on the intensity at which the households use this technology. We find that gender plays an important role in the amount of ragi flour produced; female-headed households tend to use this technology at a higher intensity than male-headed households, and households than are dominated by adult males tend to use this technology at a lower intensity than other households. We find higher intensity of use amongst households with a male in the household who is age 65 or greater. We also find that households with a greater proportion of children tend to use this technology at a higher intensity, but that the total number of children in different age categories decreases the consumption. Children age 7-12 have the least reduction on ragi flour consumption while children age 13-17 have the greatest reduction on consumption.

Our third research question asked how the prices of ragi flour, ragi grain, and wheat flour affect the adoption and intensity decisions. We find the *Price of Wheat Flour* has a negative effect on the probability of adoption. This finding was unexpected, however this result may be confounded with an income effect that may be induced by legislated prices that are reduced for households with low levels of income. As expected, we find that the production of ragi flour increases as the *Price of Ragi Flour* increases, and that production decreases as the *Price of Ragi Grain* decreases. We also find that production of ragi flour increases as the *Price of Wheat Flour* increases, indicating that wheat and ragi flour are substitutable. The policy implication of this result is that current subsidized prices for wheat flour may be crowding out demand for ragi flour, and that an increase in the subsidies for wheat will likely lead to a reduction in the amount of ragi flour consumed.

Regarding our fourth research question – how do the travel costs of accessing these mills affect household's decision to adopt the milling services? – we confirmed our expectations that travel costs would reduce the probability that households would adopt this technology. This suggests that decision makers could potentially increase the adoption of this technology through the establishment of additional mills in areas that have poor access to milling services.

In our exploratory analysis we found that there was a higher rate of adoption amongst wealthier households and amongst households that live in close proximity to the mills. We also found that the mills tend to be located closer to wealthier households. We questioned whether the higher uptake of this technology amongst wealthier households was due to a higher propensity of wealthier households to adopt, or due to other factors such as the placement of the mills. In our multivariate analysis we found that wealthier households do not have a significantly higher propensity to adopt this technology after controlling for confounding factors such as the *Travel Cost Index*. This suggests that the higher uptake of this technology by the wealthy may be due in part to the placement of the mills in close proximity to wealthier households.

We also investigated patterns of self-selection. We found evidence indicating that households that are disadvantaged – based on unobserved characteristics – may have a higher propensity to adopt this technology. It is possible that the disadvantaged households in our sample may also have lower levels of wealth. If the disadvantaged households do tend to have lower levels of wealth, then our results suggest that the technology is systematically being placed farther away from the households that this intervention was intended to target, and who have the highest propensity to adopt this technology. Given that the SHGs were responsible for the placement of these mills, our results suggests that some conditions exist that encourage SHGs to place the mills closer to wealthier households. One possible explanation is that SHG members may decide on the placement of the mills to maximize profits, which is potentially better facilitated by placing the mills in closer proximity to wealthier households. Another possible explanation is that SHGs with wealthier members may be in a better financial position to assume the risk of operating a flour milling business and may choose to establish the mills in their own communities, which may also happen to contain wealthier households. Regardless of the specific incentives at work, our analysis suggests that using SHGs to implement this technology does not result in high rates of adoption amongst disadvantaged households with lower levels of wealth. Given that tribal peoples tend to be the most disadvantaged groups in India, one may argue that, on a national scale, this intervention is benefitting disadvantaged households. However, this technology, as implemented by SHGs, may not target the most disadvantaged households within a community. Despite any other merits that this intervention might otherwise deserve, our results suggest that this intervention may not be an appropriate development tool for targeting the least wealthy and most disadvantaged households in rural India.

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Table 1: Variable Definitions and Predicted Signs

	Definition	Predicted Sign: Adoption	Predicted Sign: Intensity
Dependant Variables			
Adoption (A_i)	Dummy variable; 1= household used a mill in the month previous to survey		
Intensity (Q_i)	$= \ln(\frac{kg.\ of\ ragi\ flour\ produced\ in\ one\ month}{adult\ equivalent\ household\ size^{1}})$		
Independent Variables			
Cultivates Ragi	Dummy variable; 1= household cultivated ragi in the year previous to the survey	+	
Travel Cost Index (Distance to Mill × Elevation Gain)	Euclidean distance between the household and the mill, multiplied by difference in elevation*	−	
Household wealth index	Asset index, divided by adult equivalent household size*	+/−	+/−
Female Head	Dummy variable; 1=female head	+	+
Literate head	Dummy variable; 1= head is literate	+	+
Female head × Literate head	Interaction term; 1= head is female and literate	+	+
Widowed Head	Dummy variable; 1= head is widowed	+/−	+/−
Male dominant household	Dummy variable; there are more adult males in the household than adult females	−	−
Proportion of household members that are children	Number of children, divided by household size	+/−	+/−
Number of Children Age 0-6	Number of children in household aged 6 and below	+/−	+/−
Number of Children Age 7-12	Number of children in household aged 7-12	+/−	+/−
Number of Children Age 13-17	Number of children in household aged 13-17	+/−	+/−
Senior Male in the Household (65+)	Dummy variable; 1=at least one household member is male and age 65 or older	+/−	+/−
Senior Female in the Household (65+)	Dummy variable; 1=at least one household member is female and age 65 or older	+/−	+/−
Buys Ragi Flour	Dummy variable; 1= household purchased ragi flour in the month previous to the survey	−	−
Price of Ragi Flour	Price of ragi flour available to household (INR/kg)	+	+
Price of Ragi Grain	Price of ragi grain available to household (INR/kg)	−	−
Price of Wheat Flour	Price of wheat flour available to household (INR/kg)	+	+
λ_i	Inverse Mill's Ratio (Heckman's Lambda)		

*See appendix for the construction of this variable

Table 2: Summary Statistics of Variables from the random sample

	Mean	Minimum	Maximum	Standard Deviation
Dependant Variables				
Adoption (A_i)	0.24			0.43
Intensity (I_i)	0.56	-1.31	1.61	0.57
Independent Variables				
Cultivates Ragi	0.10			0.31
Travel Cost Index	0.17	1.66×10^{-4}	0.53	0.18
Household wealth index	1.49	0	9	0.91
Female Head	0.11			0.31
Literate head	0.66			0.47
Female head × Literate head	0.04			0.19
Widowed Head	0.11			0.32
Male dominant household	0.22			0.42
Proportion of household members that are children	0.37	0	1.33	0.33
Number of Children Age 0-6	0.36	0	3	0.65
Number of Children Age 7-12	0.41	0	3	0.64
Number of Children Age 13-17	0.31	0	2	0.55
Senior Male in the Household (65+)	0.06			0.23
Senior Female in the Household (65+)	0.07			0.26
Buys Ragi Flour	0.37			0.48
Price of Ragi Flour	23.09	1	34	7.92
Price of Ragi Grain	15.07	3	34	4.71
Price of Wheat Flour	15.53	1	40	8.50

Table 3. Results from Two-Stage Adoption Model

	Adoption[1]		Intensity	
Cultivates Ragi	0.47	***		
Travel Cost Index (Distance to Mill × Elevation Gain)	-0.41	***		
Household wealth index	0.03		0.12	***
Female Head	0.18		0.83	***
Head is Literate	-0.07		0.13	*
Female Head × Head is Literate	-0.13		-0.42	*
Widowed Head	-0.11		-0.33	**
Male Dominant Household	0.07		-0.14	*
Proportion of household members that are children	-0.12		1.35	***
Number of Children Age 0-6	0.05		-0.36	***
Number of Children Age 7-12	0.05		-0.33	***
Number of Children Age 13-17	-0.05		-0.38	***
Senior Male in the Household (65+)	0.07		0.29	**
Senior Female in the Household (65+)	-0.03		0.00	
Buys Ragi Flour	0.03		-0.26	***
Price of Ragi Flour	6.89×10^{-4}		0.02	***
Price of Ragi Grain	-0.01		-0.03	***
Price of Wheat Flour	-0.01	**	0.02	***
λ_i			-1.70	*
Constant	0.00		-0.11	

= significant at the 90% confidence level; **=95%; *=99%*

[1] Marginal effects reported.

Figure 1. Nonparametric regression of household wealth on the proportion of households that adopted the milling technology for the production of ragi flour

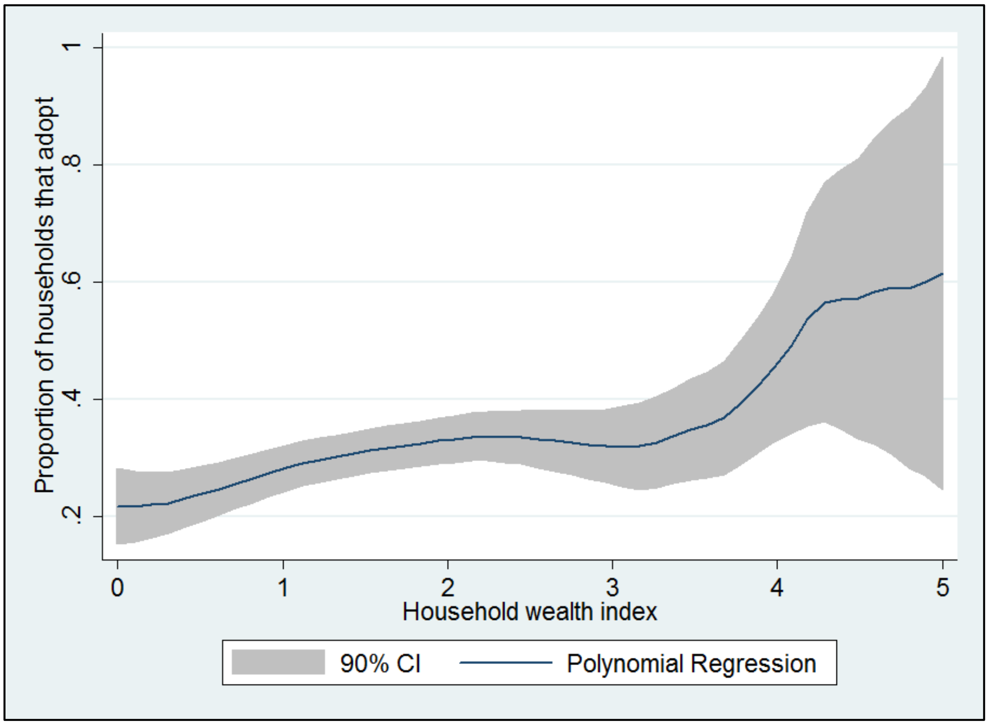


Figure 2. Nonparametric regression of travel cost on the proportion of households that adopted the milling technology for the production of ragi flour

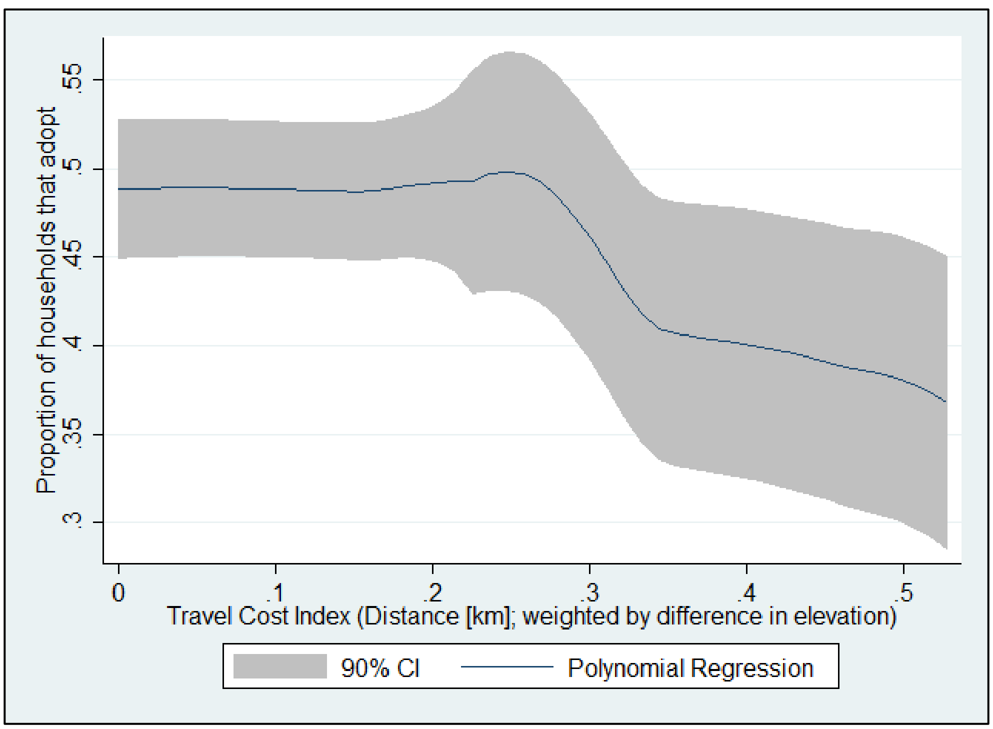
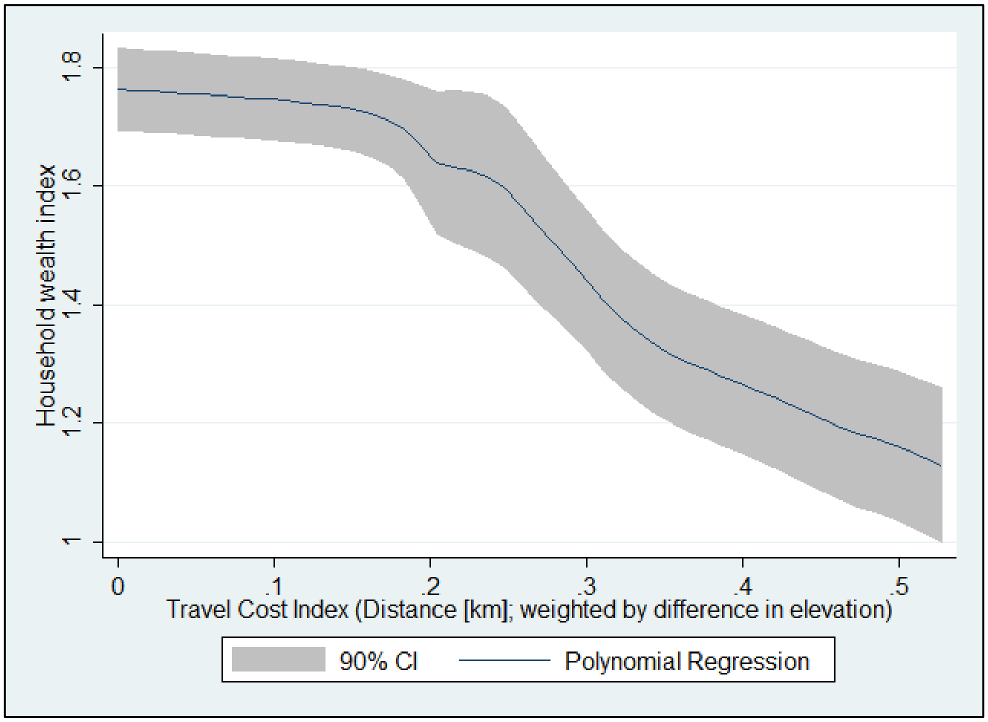


Figure 3. Nonparametric regression of household wealth and the travel costs



Appendix: Constructed Variables

Adult Equivalent Household Size

Household size is an important demographic variable which affects income and consumption. In studying the consumption and production decisions of households, it is often necessary to control for variations in household size. Although household size can be calculated by adding the number of individuals in a household, this method does not account for the heterogeneity in the composition of ages of household members between different households. Because levels of consumption and the potential for income generation may differ between adults vs. children, a more useful measurement of household size is one which accounts for the heterogeneity of ages within the household. This is often achieved by the use of an adult equivalence scale, which assigns weights to members of certain age classes, before calculating the size of the household. To calculate the adult equivalent household size, we adopted the same adult equivalency scale that is used by Glewwe and van der Gaag (1990), which assigns a weight of 0.2 to children 0-6 years old, 0.3 to children 7-12 years old, 0.5 to children 13-17 years old, and 1 to persons age 18 and greater. While this variable is not included directly in any of our regressions, it is used to create per capita measures of other variables to control for differences in household size.

Household wealth

Because measures of income in subsistence-based economies are volatile, costly to collect, and prone to measurement error, it is often advantageous to substitute annual income for a variable which is both easy to measure and highly correlated with long term income levels. One such measure is the household assets index that is used by the India Human Development Survey (Sonalde *et al.*, 2008; page 18). Adapting this measure, we constructed an index variable based on several questions regarding household ownership of certain assets and housing materials. The measure used by the IHDS was deemed to be appropriate because it was developed within an Indian context and because of the strong evidence that household asset scales reflect the long-term economic level of the household.

The household asset scale used by the IHDS sums 30 binary variables regarding household assets. Because our survey did not collect the same list of variables, our measure of household assets sums those variables used by the IHDS assets index that were collected, plus a few additional assets. When choosing which assets to include, we used the same key criterion used by the IHDS to maintain consistency. The criterion is that the measure could only include assets that are strictly indicators of wealth. Car ownership, for example, is an indicator of wealth because less wealthy households would be unable to afford a car. On the other hand, the ownership of implements such as a hoe or spade is not strictly an indicator of wealth; while it is true that households with very low levels of wealth may not be able to afford these implements, very wealthy households who do not participate in manual labour may also not own these assets. Because non-ownership of these tools may indicate either high or low levels of household wealth, they could not be included in the index. This criterion was similarly applied to the other variables which were collected in our survey. Table 4 lists the variables used by the IHDS assets measure and the variables used in our study for comparison. To control for differences in household size, we divided this sum by the *Adult Equivalent Household Size* to create a per capita measure of household wealth.

Table A: Comparison of household assets and housing variables used by the IDHS and this study to create the variable *Wealth Index*

Variables used by the IDHS	Variables used in our study	Mean
Any vehicle	Any vehicle	31%
Sewing machine	Sewing machine	0.8%
Mixer / grinder	Mixer / grinder	21%
Motor vehicle	Motor vehicle	27%
Any TV	Any TV	90%
Air cooler / cond		
Clock / watch		
Electric fan		
Chair / table		
Cot		
Telephone	Telephone	0.4%
Cell phone	Cell phone	65%
Refrigerator	Refrigerator	0%
Pressure cooker	Pressure cooker	5%
Car	Car	2%
Air conditioner		
Washing machine	Washing machine	0%
Computer	Computer	0.8%
Credit card		
2 clothes		
Footwear		
Piped indoor water		
Separate kitchen		
Flush toilet		
Electricity		
LPG		
Pucca wall	Pucca wall	80%
Pucca roof		
Pucca floor	Pucca floor	81%
	Radio	0%
	DVD player	3%
	Tape player	0.8%

Travel Cost Index

We expect proximity to a mill to significantly affect the decision to adopt this technology because there are greater costs associated with travelling longer distances. For the majority of people in our study, these costs are largely costs associated with the effort of walking. Distance to the mill was calculated as the Euclidean distance between the household and the nearest ragi mill, in kilometres. Changes in elevation increase the difficulty of walking over a given distance; Katch and McArdle (1993) show that caloric expenditures of walking are an increasing function of terrain inclination. Because our study site is hilly, we hypothesized that difference in elevation between the household and the mill would also affect the decision to adopt. Elevation from the household to the mill was calculated as the absolute value of the difference between the elevation of the household and the nearest ragi mill, in kilometres. To account for the added difficulty that is introduced by changes in elevation, we multiplied the distance from the household to the mill by the difference in elevation between the household and the mill. To avoid this weighting variable being equal to zero for households that were located at the same altitude as the nearest mill, we added one metre (0.001 km) to the difference in elevation for all households. This distance was thought to be small enough that it would not significantly affect our estimation, while at the same time it would avoid the weighted distance from being equal to zero.