Who is Buying? Fuelwood Collection in Rural India

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Abstract

Fuelwood collection is often cited as the most important cause of deforestation in many developing countries. There is a significant literature on fuelwood markets but almost no studies on who is using the fuelwood collected. Is the fuelwood collected in rural areas used locally or by people living in nearby towns and cities? The answer to this question has implications for both environment and energy policy. We study this issue by looking at the effect of reduced forest cover on the time allocation of buyers and sellers of fuelwood in rural India. We instrument time spent in fuelwood collection by the time it takes to travel from their home to the collection site. By matching two different datasets, we can identify households that buy fuelwood for their own use and those who sell fuelwood in markets. We see a clear difference in the time allocation of these two groups in response to costlier access to forest resources. When the forest is further away, fuelwood is scarce, and sellers decrease their time invested in self-employment activities. Buyers show no such trend in their behavior. Closer to town, sellers increase their collection effort, because fuelwood is likely to fetch higher prices. Buyers do not exhibit the same pattern. By differentiating buyers from sellers, we find that the number of fuelwood sellers rises closer to town and controlling for population, fuelwood sales increase. The main contribution of the paper is in disentangling fuelwood markets into those who buy and those who sell. We can therefore estimate an excess supply function of fuelwood as a function of distance from town. The main policy implication of the study is that fuelwood collection is likely driven not only by rural household demand but by demand from towns in close proximity. Thus energy policies that address deforestation and rural energy use need to target urban energy use as well.

JEL classification: O12, O18, Q48

Keywords: Deforestation, Rural Development, Time Allocation, Energy Markets, Developing Countries

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1 Introduction

Fuelwood collection is a major source of deforestation in developing countries. In populous South Asia demand for fuelwood ranks ahead of other demands for forest products such as furniture and paper as the main factor behind deforestation (Foster and Rosenzweig, 2003). Several studies have focused on fuelwood collection by households and the effect of wood price on household collection behavior Cooke (1998b); Kumar and Hotchkiss (1988); Bandyopadhyay et al. (2011); Baland et al. (2010). However, there are no careful analysis of who is buying the fuelwood collected by households. How much of the fuelwood is being consumed locally in the village and how much of it is shipped to nearby markets, especially in urban areas? Even though fuelwood has a low value to volume ratio, it can be shipped economically to markets say 10-20 kilometers away.

This paper aims to address this issue by studying the effect of reduced forest cover on the time allocation of buyers and sellers of fuelwood in rural India. We instrument time invested in fuelwood collection by the distance (measured in minutes) from the household to the resource collection site. The intuition is that if reaching the collection location takes longer, more time must be invested in collection. By matching two different datasets, we can identify households that buy fuelwood for their own use and those who sell fuelwood in markets. We see a clear difference in the responses of these two groups to a change in the availability of forest resources.

Farther from town, sellers reduce their collection effort, because the price they get is likely to be lower in villages away from the urban market because of transport costs. However, buyers exhibit no such pattern in their behavior. Higher travel times to collection locations induce fuelwood sellers to increase the time spent in collection and invest less in self-employment in order to benefit from higher wood prices. Buyers spend more time in wood collection but do not change their labor supply significantly.

By matching two different datasets at the district level, we can also predict which households buy and which sell fuelwood. We can then estimate the aggregate volume of fuelwood bought and sold as a function of the their distance from the nearest town. We find that the excess supply function for each village declines with distance from the town. Since we net out the consumption of fuelwood in each village, we infer that this net supply of fuelwood out of the village is likely being shipped to urban markets in the nearest town.

The main contribution of the paper is in partitioning rural fuelwood markets into households who buy and those who sell. The implication is that fuelwood collection is likely driven not only by rural household demand but by demand from towns in close proximity. Thus energy policies that address deforestation and rural energy use must account for urban energy use as well. For instance, high rates of deforestation may be controlled by increasing energy access and targeting pricing policies to people living in towns and informal sectors of cities.

The literature on the impact of deforestation on individual decision-making is sparse. Foster and Rosenzweig (2003) carefully examine the relationship between local income and population and growth of forests in India, and find that a rise in local demand for forest products may be positively associated with local afforestation. Other papers examine the relationship between fuelwood collection and the labor market. Because of data availability, the majority of these papers focus on Nepal. Amacher et al. (1996) show that labor supply is related to the household's choice to collect or purchase fuelwood. In their study, Nepalese households living in the Terai region who buy fuelwood are responsive to an increase in fuelwood prices and alternative labor opportunities.When fuelwood prices rise, they switch out of buying it and spend more time collecting. However, households that collect do not react with the same speed to a change in the price. Kumar and Hotchkiss (1988) examines the negative impact of deforestation on farm labor supplied by women.[1]

Section 2 develops a simple model of a household choosing between collecting, buying and selling fuelwood. In section 3 we discuss the data used in the analysis. Section 4 focuses on the empirical approach and results. In section 5 we perform some robustness tests and section 6 concludes the paper.

2 A Simple Model of Fuelwood Collection by Households

In this section, we model the choice of a household denoted i that allocates time in collecting fuelwood either for domestic consumption or for sale. Since members of the hosusehold may make these decisions to collect or work jointly, we consider all decisions at the aggregate level of the household. Heterogeneity across households in terms of time endowments and skill level etc are captured by the subscript i. Members of the household can walk to the nearest forest and collect fuelwood which can be used to meet energy needs within the household or sold in the nearest town at a fixed price p. This price is determined by

[1] Other studies have focused on water collection. Ilahi and Grimard (2000) model the choice of women living in rural Pakistan between water collection, market-based activities and leisure. The distance to a water source has a positive impact on the proportion of women involved in water collection and has a negative impact on their participation in income-generating activities.Lokshin and Yemtsov (2005) shows that rural water supply improvements in Georgia between 1998-2001 had a significant effect on health but not on labor supply. Koolwal and van de Walle (2013), using a cross country analysis, find no evidence that improved access to water leads to greater off-farm work for women. Unlike fuel, however, water has no substitute and demand is likely to be more inelastic.

equating supply and demand of fuelwood in the town.[2] Villages are small relative to towns hence individual households or villages are not able to affect the price of fuelwood. Let the distance of the village from the nearest town be denoted by x and the unit transport cost of fuelwood be given by v. Then the price in a village x kilometers away from the town can be written as $p - vx$, assuming linearity of transport costs. The price of fuelwood declines farther from the town with distance.

The household may consume fuelwood and an alternative energy source for cooking, such as kerosene or Liquefied Petroleum Gas (LPG) (or animal dung or agricultural residue), denoted by the subscript k. Utility for household i is given by $U_i(q_f + \theta q_k)$ where $U_i(\cdot)$ is a strictly increasing and concave function which suggests that a higher consumption of fuel wood increases utility but at a decreasing rate. Here q_f and q_k are quantities of fuelwood and kerosene consumed by the household each time period, say a week. The alternative fuel may have a different energy efficiency, which is represented by the parameter θ. For now, we do not specify whether θ is smaller or larger than one. If this fuel is kerosene, θ is likely to be greater than unity because it is more energy-efficient than fuelwood. However if it is crop residue, it may be a value smaller than one. Household-specific characteristics such as income or size may affect the shape of the utility function, and they are captured by the subscript i. Each household is endowed with $\bar{t}_i$ units of time and the reservation wage of the household is given by $\bar{w}_i$ - more educated households may earn a higher wage, for instance. The household allocates time between collecting fuelwood and working for wages so that

$$t_w + t_c \leq \bar{t}_i, \tag{1}$$

where t_c is the time spent collecting fuelwood and t_w is time spent in wage labor.[3]

Let f_i be the volume of fuelwood collected per unit time. This includes the time spent traveling to the forest site and returning home. Since households differ in their location, this variable captures their different travel times to the collection site, which may be outside the village boundary. Each household can decide whether to collect fuelwood, and if so, the quantity it will collect. If it collects more than what it needs, it can sell the surplus fuelwood in the urban market at the given price $p - vx$. The price of the alternative fuel (e.g., kerosene) is taken as constant and given by p_k.[4] The maximization problem of the

[2] We abstract from considering multiple towns in close proximity to a village. However, we re-visit this point later in the empirical section.

[3] Here we abstain from considering household size.

[4] The price of kerosene may actually increase away from the town if the distribution center is located there. We discuss this issue later.

household can then be written as

$$\max_{q_f, q_c, q_k, t_w} U_i(q_f + \theta q_k) + \bar{w}_i t_w + (p - vx)(q_c - q_f) - p_k q_k \tag{2}$$

subject to (1) and $q_c = f_i t_c$. The choice variables are the time spent in collecting fuelwood t_c and working for wages t_w, and the quantity of fuelwood and alternative energy consumed - q_f and q_k. Let us attach a Lagrangian multiplier λ to the inequality (1) to get

$$L = U_i(q_f + \theta q_k) + \bar{w}_i t_w + (p - vx)(q_c - q_f) - p_k q_k + \lambda(\bar{t_i} - t_w - t_c). \tag{3}$$

which yields the first order conditions

$$U_i'(\cdot) \leq p - vx \ (= 0 \text{ if } q_f > 0) \tag{4}$$

$$\theta U_i'(\cdot) \leq p_k \ (= 0 \text{ if } q_k > 0). \tag{5}$$

Note that if the price of fuelwood in the village $p - vx$ is high, the household will consume relatively small amounts of it. If the household consumes positive amounts of kerosene to complement its use of fuelwood, then (5) must hold with equality, so that the condition $U_i'(\cdot) = \frac{p_k}{\theta}$ must hold. For kerosene, the value of θ is likely to be greater than one. Hence, for a household to use both fuels, the price of fuelwood should be lower than the price of kerosene, or $\theta(p - vx) = p_k$. If kerosene is too expensive, the household will use only fuelwood if the latter is cheaper, or $U'(\cdot) = p - vx < p_k$. The remaining necessary conditions are

$$(p - vx) f_i \leq \lambda \ (= 0 \text{ if } q_c > 0) \tag{6}$$

$$\bar{w}_i \leq \lambda \ (= 0 \text{ if } t_w > 0). \tag{7}$$

From (6), if the household collects then it must be the case that $(p - vx) f_i = \lambda$, that is, the collection of fuelwood per unit of time on the left of the equation must equal the shadow price of time, denoted by λ. If the shadow price of time is relatively low, which may be the case, for example, if the household labor endowment is high (a larger family, for example), then λ is likely to be lower, in which case the time spent collecting would be high. If the household collects a lot of fuelwood, they may consume a small fraction and sell the rest, which adds to their utility in the form of increased revenue. The trade-off between working to earn wages and collecting is shown in equation (7). Equality implies that the household allocates time to wage labor. If wages are too low, then $\bar{w} < \lambda$ in which case, $t_w = 0$ and the household spends all its time collecting fuelwood.

The above decisions are sensitive to the location of the village where the household resides, with respect to the nearest town where fuelwood is shipped. If it is remote relative to the town where the fuelwood is sold, households face a the same price for fuelwood in the town p but a lower price net of transport costs, given by $p - vx$. *Ceteris paribus*, we should expect to see less fuelwood being supplied by sellers, and more time allocated to alternate wage-earning jobs such as working longer hours in the family farm or in other industries. For buyers of fuelwood, the price is lower, hence they should buy more of it.

The intuition behind these relationships is shown in Figure 1. The top panel shows that the price of fuelwood falls with distance from the nearest town. The horizontal line represents the reservation wage of the household. Households for whom the price of fuelwood is higher than their reservation wage collect to sell fuelwood. Those for whom the price of fuelwood is lower than the reservation wage, find more profitable to work in alternative occupations. These decisions are idiosyncratic to households in the same village, because their wage rates may differ due to education, skill set or other characteristics. Now consider a region with a lower endowment of forest cover (bottom panel). A lower forest stock leads to an increase in the price of fuelwood because of scarcity. All else the same, a lower forest stock raises the price of fuelwood and induces more collection. With a lower forest stock, farther from town, the price of wood is high and there is less incentive to ship the wood to the town where the price is fixed. Buyers are willing to pay a higher price. This may also be true if the price of alternative fuels is higher in remote locations.

Although we do not explicitly model heterogeneity among households here, it is clear that not only will households differ in terms of their location and travel costs, but also their time endowment and reservation wage. For example, a household with more skilled labor may enjoy a higher wage, in which case, they may only buy fuelwood. On the other hand, a low skilled household from the same village, may collect and sell. The same logic works when households differ, say by their size. More members of working age may imply a higher endowment of labor, leading to more collection.

We can summarize these results as follows:

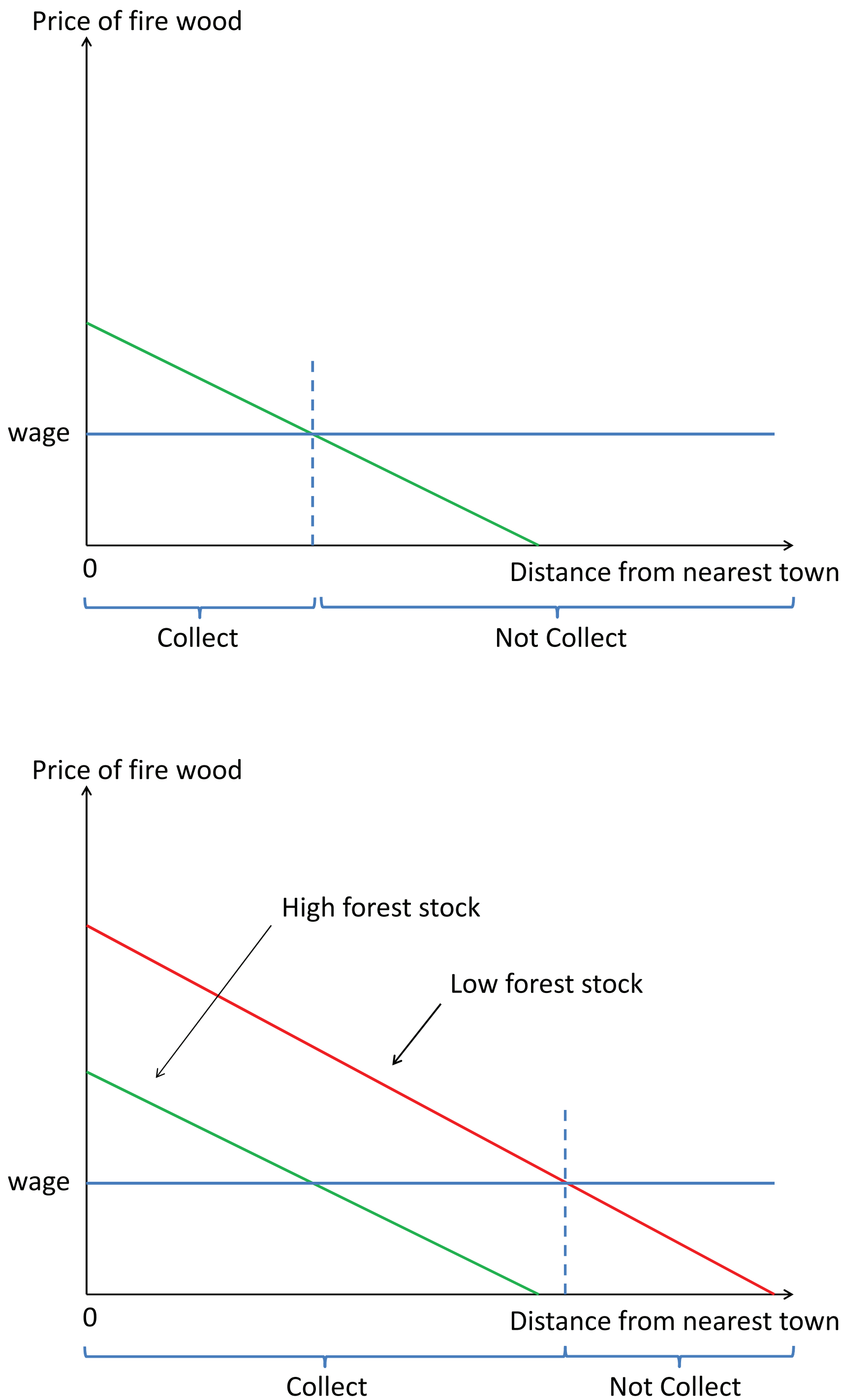
Proposition 1: *The price of fuelwood in the village decreases with distance from the nearest town.*

Proposition 2: *The price of fuelwood is higher closer to town, hence sellers of fuelwood located there supply more, while buyers buy less.*

Proposition 3: *Farther from the city, more time is invested in occupations others than fuelwood collection.*

Proposition 4: *Scarce forest resources will increase the price of wood, hence sellers*

Figure 1: Price of fuelwood as a function of the distance from the nearest town, with high and low stock of forest



will supply more and buyers buy less. Sellers will work less in wage occupations. Buyers may respond to large price increases by working more to pay for expensive energy.

3 Data

We use the Indian Human Development Survey (IHDS), which is a nationally representative cross-sectional dataset. This survey was done during 2004-05 and contains information at the individual, household and village level for 41,554 households living in urban and rural areas. We focus our attention exclusively on the 26,734 rural households.[5]

Table 1 reports descriptive statistics for the variables employed in the empirical analysis. About 90% of the households in our sample collect fuelwood, while 97% are involved in some kind of labor market activity. About 77% of households are engaged in wage labor. The typical adult in the household spends nearly three hours per week in fuelwood collection and 21 hours in the labor market. These hours are split into 13 hours in wage labor and eight hours in self employment. The average travel time per trip between the household location and the forest site is 38 minutes with a high standard deviation of 34 minutes.

Households have an average of 5.36 members including children below 15 years of age. Roughly 66% of the household consists of members who are older than 15 years and younger than 65. The head of the household has almost 4 years of education and households are predominantly Hindu. 61% of the households in our sample are connected to the electric grid, 94% use kerosene, while a much smaller fraction - 11% and 24% use LPG and crop residue, respectively. Fuelwood use is widespread - about 95% of the households use it. Villages tend to be located close to towns, with a mean distance of 15.14 km. The majority of the households live in villages with a population smaller than 5,000. Fuelwood prices vary significantly across villages, with a mean price for households of Rs 1.68/kg. Unskilled males earn about a third higher wages than females.

Even though our analysis takes place at the household level, it is useful to see the division of labor within the household. Table 2 reports the proportion of respondents by gender who participate in the labor market and are involved in wood collection. Close to 85% of the women are involved in collection and a third of all women participate in the labor market. Only 4.3% of the women are involved in the labor market but not in fuel collection. The picture is somewhat different for men. Less of the men (58%) collect fuelwood and 54% are involved in the labor market. About a third of the men (32%) participate in the labor market and collect fuelwood.

[5]The survey is representative at the national level, but not necessarily for smaller geographical units.

Table 1: Descriptive statistics: Household and Village

Variable	**Mean**	**St. Dev.**	**Min**	**Max**
Share of households collecting	0.90	0.29	0.00	1.00
Time spent collecting per adult (hours/week)	2.74	2.84	0.00	36.00
Share of households in labor market	0.97	0.17	0.00	1.00
Share of households working for wages	0.77	0.42	0	1.00
Time spent in employment per adult (hours/week)	21.05	12.23	0.00	95.48
Time spent working for wages per adult (hours/week)	13.43	12.00	0.00	72.31
Time spent in self-employment per adult (hours/week)	7.62	10.08	0.00	85.96
Travel time to forest site (minutes/trip)	38.43	33.87	0.00	240
Size of household	5.36	2.56	1.00	38.00
Share of Household between 15 and 65 years of age	66.22	22.12	12.50	100.00
Years of education of head of household	3.64	4.15	0.00	15.00
Household income per cons unit (Rs)	11,773	16,209	2.26	830,000
Share of Hindu households	0.88	0.33	0.00	1.00
Share of households involved in conflict	0.43	0.49	0.00	1.00
Share of households with electricity connection	0.61	0.49	0.00	1.00
Share of households using fuelwood	0.95	0.22	0.00	1.00
Share of households using crop residue	0.24	0.43	0.00	1.00
Share of households using kerosene	0.94	0.24	0.00	1.00
Share of households using LPG	0.11	0.31	0.00	1.00
Price of fuelwood in village (Rs/kg)	1.68	2.96	0.01	40.00
Share of villages with an employment program	0.88	0.32	0.00	1.00
Distance of village to nearest town (in km)	15.14	11.71	1.00	85.00
Population of village (1,001-5,000)	0.58	0.49	0.00	1.00
Population of village above 5,000	0.19	0.39	0.00	1.00
Average wage in village for unskilled labor (Rs/day)	52.09	27.58	6.00	524.50
Average wage in village for unskilled labor: male (Rs/day)	60.11	45.55	6.00	999.00
Average wage in village for unskilled labor: female (Rs/day)	44.07	17.91	6.00	150.00

Notes: We have 10,169 households. The price of fuelwood is observed only for 8,738 of them. Time spent in employment equals time spent working for wages plus in self-employment. LPG is Liquified Petroleum Gas.

Table 2: Fuelwood collection and labor force participation by gender

	Not participating in labor force	Participating in labor force	Total
Women			
Not collecting	11.32%	4.27%	15.59%
Collecting	51.94%	32.48%	84.41%
Total	63.25%	36.75%	100%
Men			
Not collecting	20.19%	22.13%	42.32%
Collecting	25.66%	32.02%	57.68%
Total	45.85%	54.15%	100%

Roughly a fifth of our sample live in districts which lost forest cover between 2000 and 2004. This information is taken from the Forest Survey of India reports (2001, 2005), which covers 368 districts.[6] In 2004, national forest cover was estimated at 20.6% (Forest Survey of India, 2005).[7] Figure 2 shows the variation in forest cover by district.[8] For example, the state of Haryana has only a 4% cover, while Lakshadweep has 86% coverage. Most of the deforestation has occurred in areas with dense coverage (a canopy density higher than 40%), while open forests (canopy density between 10-40%) are increasing (see Table A.1). Figure 3 shows that some districts have experienced significant deforestation during the period 2000-04. About 40% of the forest cover has degraded to some degree.

4 Empirical Approach and Results

4.1 Identification

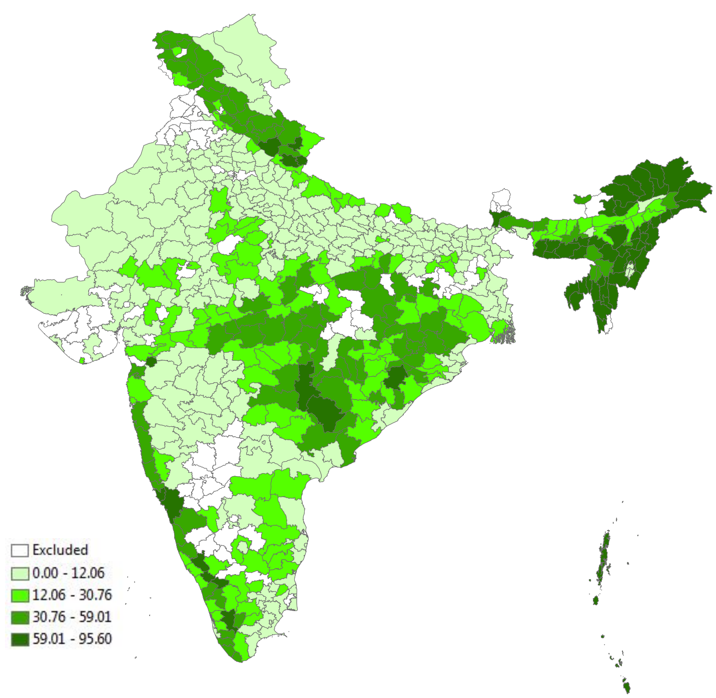
Fuel collection decisions depend on factors that may contemporaneously affect labor market participation. For example, a household may be living in an area which is growing faster. Therefore, its members would probably earn higher wages and collect less. Because of this correlation between the variable of interest and the error term, a simple Ordinary

[6]These reports contain bi-annual forest cover and deforestation data by state and district, processed from satellite images from 2000 and 2004 using GIS at a scale of 1:50,000.

[7]The mean district forest cover was $1,100 km^2$, and mean district surface area was $5,800 km^2$.

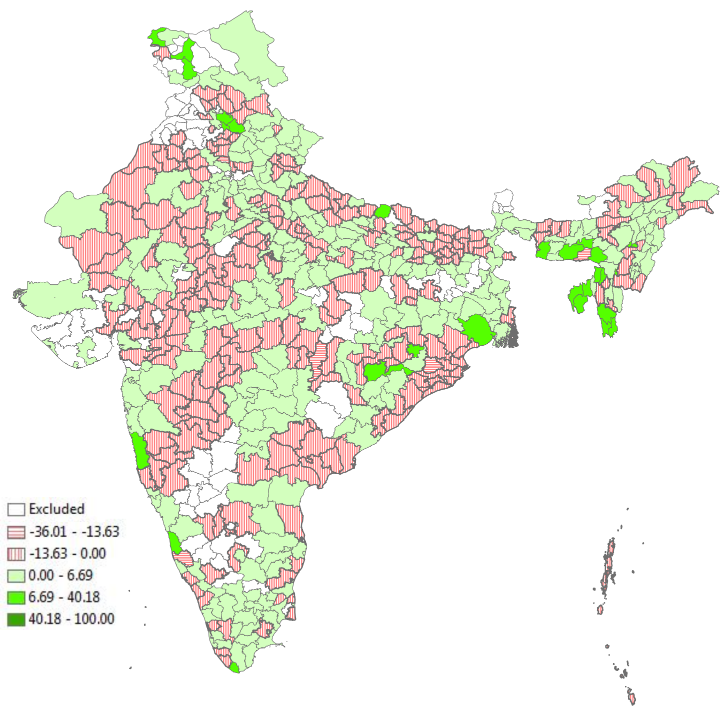
[8]Table A.1 reports forest cover for all states for 2000 and 2004.

Figure 2: Forest cover by district in 2005



Notes: The numbers represent percent of district area under forest cover.
Source: ESRI ArcGIS World Package, Geocommons and 2005 Forest Survey of India.

Figure 3: Deforestation by district between 2000 and 2004



Notes: The numbers represent percent variation of forest cover.
Source: ESRI ArcGIS World Package, Geocommons, 2001 and 2005 Forest Survey of India.

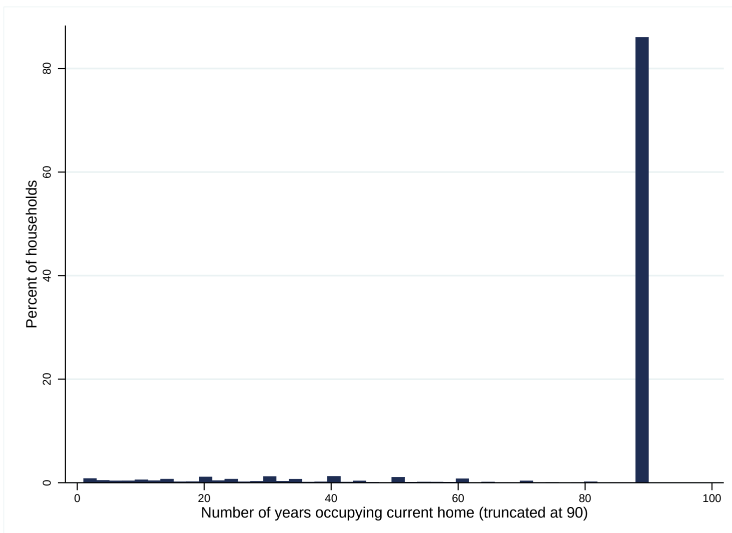
Least Squares (OLS) regression will fail to identify a causal relationship. We deal with this endogeneity problem by using an instrumental variables approach. We instrument the time spent in fuelwood collection with the distance (measured in minutes) between the household and the collection site. The idea is that if there is less forest cover near a village, it takes longer for the residents to get there to collect fuelwood. We can make several arguments to justify why travel time may be a good instrument. First, the mean district-level distance from the household to the collection location is negatively correlated with the degree of deforestation in the district between 2000-2004.

An increase in the distance is indeed correlated with a decrease in the forest cover between 2000 and 2004. In this way, we are able to isolate the variation in collection time which is due to the degradation in the availability of forest products and in this way identify a casual relationship between a change in the time spent in collection and a change in the time spent in the labor market. As stated above, data on the variation of forest cover (i.e. deforestation or reforestation) are available only at the district level. Therefore, using the distance to the collection location allows us to capture at least part of the variation in forest cover within districts. As shown in Table 1, this variable exhibit a large variation across households, with an average travel time of 38 minutes and a standard deviation of 34 minutes.

In order to understand the nexus between deforestation and the time spent in collection one has to remember that deforestation does not simply imply less forest cover, but it also implies a less dense canopy for the remaining forest. A direct consequence of a less dense forest canopy is that it will take longer in order to collect the same amount of fuelwood. The identifying variation of our empirical specification comes from these changes.

One could argue that the location of a house may be endogenously determined – household members can change their location, for instance, if the distance to the forest becomes relatively large. However, this argument may not hold in the Indian context. The Indian rural real estate market is virtually nonexistent. In 2001, 95.4% of the rural households owned the house they were living in (Tiwari, 2007). This very high rate of home ownership, which can also be observed in our dataset, has been relatively stable over the last four decades. The majority of these houses are built by residents themselves and not bought in the market. It is difficult to obtain financing in rural India. Between 55% and 80% of the money spent annually in rural real estate is devoted to home alterations, improvements and major repairs. All these facts taken together tell us that rural Indian households do not move often from their location. Once a household settles into a location, it is likely to stay there for generations. The proportion of entire households migrating is 1.6% of the total, according to the 2001 census, and this number may be an overestimate since it includes both urban and rural households.[9] Further proof of this comes from our own data. The survey asked when did the household first settle in the location where they are currently living. The maximum answer a household could provide was 90 years, which is the survey equivalent of *forever*. The average years of residence reported is of 83.1, implying that the majority of the households in our sample have been living in the same location for a very long time (88.5% of the household in our sample report having been in the same house for at least 90 years), confirming our hypothesis. Figure 4 shows evidence of the high number of households which have been in the same location for over 90 years.

Figure 4



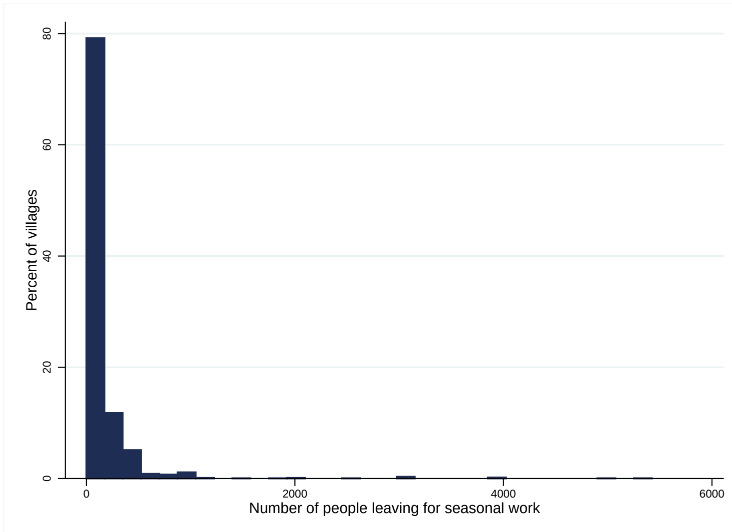
Notes: Kernel density estimation of the number of years households have lived in same house, censored at 90 years.

One could argue that even though households do not move much in the Indian context, single household members may move seasonally to cities and other regions for work. Maybe surprisingly, this is not the case. In our data we observe some seasonal migration but not much, as Figure 5 shows.

All these elements suggest that even if the placement of a house was endogenous to the location of the forest when the household first settled in the region, this may not be true anymore. As shown in Figure 3, forest cover changes significantly through the years. Therefore, we are confident in considering the distance to collection location as being exogenous to the location of the household. One could still argue that the placement of the whole village is endogenous with respect to the forest, we will take care of this issue

[9] Additional evidence on the very low mobility of the Indian population can be found in National Sample Survey Office (2010).

Figure 5



Notes: Kernel density estimation of the number of workers leaving village for seasonal work.

by having a specification including village fixed effects.

Another argument which could be raised against the validity of this instrument concerns the exclusion restriction. We may think that the placement of a house is endogenous to the profession chosen. This may be true in urban areas, where we observe spatial clustering of people by skills and income. Yet, it may be less relevant to rural India, where if anything, higher income households may have historically settled closer to higher quality farmland.

The first stage regression of our specification has the following form

$$HC_{hvd} = \alpha + \delta_d + \beta D_{hvd} + X'_{hvd}\gamma_1 + G'_{vd}\gamma_2 + +\varepsilon_{hvd} \tag{8}$$

where HC denotes the average time spent in fuelwood collection per adult (age 15-65 years) in household h; D represents the distance from the collection location and ε is an error term. Household, village and district are indexed h, v and d, respectively. Thus, δ_d represents a set of district fixed-effects, X denotes a matrix of household specific controls and G one of village specific controls.

Table 3 reports the results of the first stage estimation, equation (8). In column (1) we only control for district fixed effects in addition to the instrument. We then add a series of household composition controls in column (2) and of household energy controls in column (3). Finally, column (4) presents the full specification, where we also control for a series of village specific controls. Standard errors are robust and clustered at the

Table 3: First stage

	Dependent variable collection time (log)			
	(1)	(2)	(3)	(4)
Travel time (log)	0.286***	0.282***	0.274***	0.274***
	(0.011)	(0.011)	(0.012)	(0.012)
Households controls	no	yes	yes	yes
Energy controls	no	no	yes	yes
Village controls	no	no	no	yes
District FE	yes	yes	yes	yes
Observations	10,169	10,169	10,169	10,169
F-stat first stage	647.34	604.02	556.82	563.18

Notes: All estimations contain a constant. Standard errors in parentheses are clustered at the district level. ***p<0.01, **p<0.05, *p<0.1.

district level. The coefficient on the instrument is robust across specifications in terms of sign, magnitude and statistical significance. The results suggest that the scarcity of fuelwood generated by a reduction of the forest cover – represented by longer travel times to the forest – has a positive and statistically significant effect on the amount of time an individual spends collecting. Column (4) shows us that a 10% increase in the travel time to the forest leads to a 2.6% increase in the time spent in collection activities which, for the average household means that an increase of 4 minutes in the travel time corresponds to an increase of collection time of 4.6 minutes.[10] These impacts are statistically significant at 1%.

Table A.2 of the Appendix reports the detail of all the controls included in the regression and their respective coefficients. The sign of all the statistically significant coefficients are as expected. An increase in the household's size increases the time spent in collection, while an increase in the household's income leads to a decrease in collection time. It is plausible that as household's income increases they move up the energy ladder and switch to cleaner, yet more expensive fuels, for instance LPG. The use of crop residues has a

[10] 2.95x60x0.026.

positive impact on the time spent collecting, again this might be linked to the household's income: poor households use more crop residues and more fuelwood as sources of energy. Finally, as expected, the use of LPG has a negative impact on collection time.

We now turn to the main part of the analysis, the impact of changes in collection behavior, brought about by a degradation of the forest stock, on labor market outcomes. H denotes an individual's labor supply (measured in hours) and $\hat{HC}$ represents the fitted values coming from the first stage regression (equation 8). The specification of the second stage takes the following form

$$H_{hvd} = \alpha + \delta_d + \beta \hat{HC}_{hvd} + X'_{hvd}\gamma_1 + G'_{vd}\gamma_2 + u_{hvd} \quad (9)$$

where household, village and district are represented by h, v and d, respectively; δ_d represents a set of district dummies; X denotes a matrix of household specific controls and G of village-specific controls. Finally, u is the error term. Again, the coefficient of interest is β.

Table 4 reports results for the estimation of equation (9). We first report results for all labor market activities and subsequently split between self-employment and wage activities. The table is organized like Table 3. In column (1) we only control for district fixed effects, while in column (2) and (3) we add household composition controls and household energy usage controls, respectively. Column (4) reports our main specification, where we also control for a set of village level controls. Standard errors are robust and clustered at the district level.

Surprisingly, an increase in the time spent in collection has a positive impact on the time spent in the labor market. A 10% increase in collection time increases labor supply by 1.1%. The coefficient is statistically significant at the 1% level. For the average household, this means that an 18 minutes increase in collection raises labor supply by 14 minutes.[11] The second and third section of Table 4 show the results hours spent in self-employment and wage-employment, respectively. Note that the positive effect on overall employment comes entirely from an increase in the time spent in wage employment. A 10% increase in collection time increases time spent in wage activities by 20%, and again this result is robust across specifications and statistically significant at the 1% level. This means that a 4 minutes increase in travel time (corresponding to a 10% increase) increases the time spent in wage employment for a member of the average household by roughly 40.6 minutes. Participation in family activities is only slightly negatively affected by changes in collection behavior.

The positive effect of longer collection times on wage earning activities may, at first,

[11] 21.12x60x0.011, 18 minutes corresponds to a 10% increase in collection time (18/(2.95x60)).

Table 4: Second stage

	Dependent variable: working time (log)			
	(1)	(2)	(3)	(4)
All activities:				
Hours spent collecting (log)	0.139***	0.164***	0.115***	0.119***
	(0.040)	(0.040)	(0.040)	(0.040)
Self-employment:				
Hours spent collecting (log)	−0.226***	−0.180***	−0.159**	−0.165**
	(0.063)	(0.059)	(0.065)	(0.064)
Wage activities:				
Hours spent collecting (log)	0.409***	0.385***	0.288***	0.292***
	(0.061)	(0.061)	(0.064)	(0.063)
Households controls	no	yes	yes	yes
Energy controls	no	no	yes	yes
Village controls	no	no	no	yes
District FE	yes	yes	yes	yes
Observations	10,169	10,169	10,169	10,169

Notes: All estimations contain a constant. Standard errors in parentheses are clustered at the district level. ***p<0.01, **p<0.05, *p<0.1.

seem counter-intuitive, especially in light of earlier work by Cooke (1998a). However, as suggested by our simple theoretical model, this effect may be quite intuitive. In India, about 50% of the people living in urban areas still use fuelwood as a source of energy FAO (2010). The decline in forest cover raises the price of fuelwood, as we show in Table 5. The district-level correlation between deforestation and the price of fuelwood is of XXX. Data on the price of fuelwood are taken from the IHDS survey and are disaggregated at the village level. One may consider the price of fuelwood to be a proxy for the abundance of forest resources in the village. A decline in forest cover leads to higher fuelwood prices. A higher proportion of the district covered by forest means a lower price, as shown in Table 5.

The mean price of fuelwood is lower (13.3 Rs/10kg) in districts that did experience deforestation between 2002 and 2004 then in districts that experienced reforestation (23.6 Rs/10kg). The price difference is also significant between districts where forest cover represents less than 5% of the geographical area (22.1 Rs/10kg) and those with a higher share (13.5 Rs/10kg). The price increase has several implications. According to our model, a decrease in the forest cover leads to a rise in price, which makes resource collection more attractive. An increase in the price of fuelwood may also induce consumers (especially in nearby urban areas) to switch to cheaper alternative sources of energy such as kerosene. This process generates a negative income shock for people living in rural areas lying in the hinterland of cities who collect wood and send it to the city. This reduction in incomes from a decline in forest stock may be what is pushing more people living in rural areas toward getting wage-earning occupations. In the next section of the paper we investigate the role of cities more in detail.

It may be the case that in areas with lower forest abundance, there are higher paying jobs in forestry or related sectors such as agriculture. For example, expansion of farming may lead to a decline in forest cover and people switching to wage labor. We do observe a higher GDP from forestry in districts characterized by higher deforestation.

4.2 Demand for Fuelwood as a function of distance to nearest town

In this section we explore the relationship of the proximity of the village to the nearest urban center on the impact of a change in collection time on labor market decisions. According to the theoretical model presented in section 2, we expect the behavior of net sellers of fuelwood to differ from the behavior of net buyers of fuelwood. The difference should be starker when we consider their distance from the closest urban center. Since the majority of the fuelwood sold is going to urban centers, the further from it, the less interesting it

Table 5: Relationship between forest cover and fuel wood price

	Fuelwood price (Rs/kg)
Forest cover $< 100km^2$	2.537
Forest cover $> 100km^2$ and $< 500km^2$	1.460
Forest cover $> 500km^2$ and $< 1500km^2$	1.392
Forest cover $> 1500km^2$	1.386
Forest cover changes negatively between 2002 and 2004	1.330
Forest cover does not change between 2002 and 2004	1.611
Forest cover changes positively between 2002 and 2004	2.357
Forest cover represents less than 5% of geographical area	2.207
Forest cover represents more than 5% of geographical area	1.351

Source: Data on price of fuelwood is from IHDS, while data on district forest cover is from the Forest Survey of India (2001, 2005).

becomes to be a seller of fuelwood. The behavior of the price of fuelwood with respect to the distance from an urban center observed in our data, presented in Table 6, seems to confirm the assumptions made in the model.

Table 6: Relationship between distance from nearest town and price of fuelwood

	Distance to town $<= 20$km	Distance to town > 20km – $<= 30$km	Distance to town > 30km
fuelwood price (Rs/10kg)	17.54	14.68	13.67

The IHDS data allows us to split the sample between buyers of fuelwood and non-buyers of fuelwood. This is done using data on the amount of rupees spent on fuelwood by each household. People who do not spend any money on fuelwood can be classified as weak sellers, because they could also just be collecting enough for their domestic consumption. Later, we devise a methodology which allows us to capture only the net sellers of fuelwood. Table 7 shows descriptive statistics for the main variables for buyers and non buyers of fuelwood.

Table 8 presents first stage results for buyers and non-buyers. This table confirms the results from Table 3. While it seems that the coefficient on travel time is bigger in magnitude for buyers, 0.255 versus 0.178 for non-buyers, once we compute the impact for the average buying and non-buying household we realize that it is much stronger for the non-buying household. A 10% increase in the travel time to the forest, corresponding to 2.2 minutes for buyers and to 4.4 minutes for non-buyers, generates an increase in collection

Table 7: Descriptive statistics for buyers and non buyers

Variable	**Mean**	**St. Dev.**	**Min**	**Max**
Buyers				
Share collecting resources	0.63	0.48	0.00	1.00
Hours per week in collection	1.38	2.22	0	15.67
Share working	0.97	0.18	0.00	1.00
Share of household in the labor market	0.66	0.29	0.00	1.00
Hours per week in the labor market	19.91	11.97	0.00	86.54
Hours per week in self-employment	6.72	9.71	0.00	69.23
Hours per week in wage activities	13.19	11.72	0.00	69.23
Travel time (min)	24.28	33.46	0.00	180
Household size	5.38	2.49	1.00	19.00
Share of Household >15 and <65 years	65.90	22.60	14.29	100.00
Years of education of the head of household	4.02	4.21	0.00	15.00
Share of Women in the household	49.03	16.21	0.00	1.00
Hindu	0.83	0.38	0.00	1.00
Household income per cons unit (Rs)	12,266	12,920	80	151,400
Involved in Conflict	0.42	0.49	0.00	1.00
Electricity connection	0.65	0.48	0.00	1.00
fuelwood	1.00	0.00	1.00	1.00
Crop residue	0.21	0.41	0.00	1.00
Kerosene	0.95	0.23	0.00	1.00
LPG	0.15	0.36	0.00	1.00
Non buyers				
Share collecting resources	1.00	0.00	1.00	1.00
Hours per week in collection	3.13	2.94	0.02	28.00
Share working	0.98	0.15	0.00	1.00
Share of household in the labor market	0.75	0.27	0.00	1.00
Hours per week in the labor market	23.03	12.71	0.00	95.48
Hours per week in self-employment	8.53	10.84	0.00	85.96
Hours per week in wage activities	14.49	12.71	0.00	72.31
Travel time (min)	45.14	32.24	1.00	180
Household size	5.40	2.65	1.00	31.00
Share of Household >15 and <65 years	66.77	21.87	12.50	100.00
Years of education of the head of household	3.48	4.09	0.00	15.00
Share of Women in the household	49.41	17.04	0.00	1.00
Hindu	0.90	0.30	0.00	1.00
Household income per cons unit (Rs)	11,635	15,908	2.26	718,750
Involved in Conflict	0.40	0.49	0.00	1.00
Electricity connection	0.69	0.46	0.00	1.00
fuelwood	0.98	0.13	0.00	1.00
Crop residue	0.21	0.41	0.00	1.00
Kerosene	0.94	0.24	0.00	1.00
LPG	0.09	0.29	0.00	1.00

Notes: We have 1,325 buyers and 5,315 non-buyers.

time by 2.5% for buyers and by 1.7% for non-buyers. Yet the impact in minutes for the average household is of an increase of 2.1 minutes for the buyers and of 3.3 minutes for the non-buyers. The results are robust across specifications and statistically significant at the 1% level. As expected, distance from the closest town does not have an impact on buyers. However, it reduces the time spent in collection for sellers, because the price they are able to fetch decreases with distance from the city, as predicted by our model. A 10% increase in the distance from the nearest town results in a decrease in collection time by 0.3%.

Table 8: First stage buyers and non-buyers

	Dependent variable: collection time (log)			
	(1)	(2)	(3)	(4)
Buyers:				
Travel time (log)	0.267***	0.265***	0.260***	0.259***
	(0.016)	(0.016)	(0.014)	(0.013)
Distance to nearest town (log)				0.053
				(0.041)
Observations	1,325	1,325	1,325	1,325
F-stat first stage	281.80	281.28	329.52	405.11
Non-buyers:				
Travel time (log)	0.196***	0.193***	0.187***	0.189***
	(0.023)	(0.023)	(0.022)	(0.021)
Distance to nearest town (log)				−0.001
				(0.030)
Observations	5,315	5,315	5,315	5,315
F-stat first stage	71.60	69.75	72.86	80.47
Households controls	no	yes	yes	yes
Energy controls	no	no	yes	yes
Village controls	no	no	no	yes
District FE	yes	yes	yes	yes

Notes: All estimations contain a constant. Standard errors in parentheses are clustered at the district level. ***p<0.01, **p<0.05, *p<0.1.

Non-buyers We next disentangle the labor market responses for buyers and non-buyers. Responses for non-buyers are shown in Table 9. As before, we present results for all activities first, and then for self and wage employment. Results for the non-buyers differ from the general results presented in Table 4. When considering all activities, we cannot capture any effect from a change in collection habits yet, when we split between self and wage employment we observe that in response to a reduction in the availability of fuelwood, non-buyers reduce the time dedicated to self employment and increase the time dedicated to wage employment. The latter was already observed for the whole sample. A 10% increase in collection time leads to a reduction of self employment by 3.2%. The decrease in self employment generated by a decrease in the availability of forest products decreases as we move further from cities, as it is implied by the positive coefficient on the distance from the nearest town. An increase in the distance from the closest town by 10% leads to an increase in the time invested in self employment by 1.1%. That is, distance from the nearest demand pole matters for weak sellers.

In order to understand why the coefficient for the impact on wage employment is much bigger in magnitude with respect to the others, we run a specification where we replace district fixed effects with village fixed effects.[12] The reason behind such a large coefficient could be related for instance to the fact that in areas characterized by a lower forest cover the average farm size is bigger and therefore there are more opportunities for wage-employment. Forest cover can change significantly within a district and therefore, district fixed effect do not capture this variation. If this interpretation is correct, the result should disappear when introducing village fixed effects, because this larger set of dummies will soak up all the variation within a district. At the same time, the village fixed effect specification also works as a robustness test for our instrument, by dealing with the possibility of an endogenous placement of villages (closer to the forest). In this case the identifying variation comes only from differences in travel time within the same village.

Table 10 reports results for the village fixed effect specification. In this case we cannot observe the impact of the distance from the closer town, since the distance is only measured at the village level. As expected the main results still hold: a reduction in forest cover increases the time invested in collection and, for non-buyers, decreases the time invested in self-employment. Yet, once we control for village fixed effects, the impact on wage employment becomes statistically non significant. This confirms our hypothesis that, in the district fixed effect specification, this coefficient was simply capturing a different labor market structure in areas characterized by high versus low levels of forest cover.

[12]Table A.3, in the Appendix, reports a specification for the whole sample with village-level fixed effects. We can observe that our baseline results are robust also to this specification.

Table 9: Second stage non buyers

	Dependent variable: working time (log)			
	(1)	(2)	(3)	(4)
All activities:				
Hours spent collecting (log)	0.063	0.073	0.036	0.035
	(0.101)	(0.096)	(0.098)	(0.098)
Distance to nearest town (log)				−0.003
				(0.022)
Self employment:				
Hours spent collecting (log)	−0.640***	−0.620***	−0.637***	−0.665***
	(0.226)	(0.224)	(0.227)	(0.218)
Distance to nearest town (log)				0.106*
				(0.061)
Wage employment:				
Hours spent collecting (log)	0.707***	0.687***	0.634***	0.638***
	(0.211)	(0.203)	(0.203)	(0.196)
Distance to nearest town (log)				−0.054
				(0.047)
Households controls	no	yes	yes	yes
Energy controls	no	no	yes	yes
Village controls	no	no	no	yes
District FE	yes	yes	yes	yes
Observations	5,315	5,315	5,315	5,315

Notes: All estimations contain a constant. Standard errors in parentheses are clustered at the district level. ***p<0.01, **p<0.05, *p<0.1.

Table 10: Non-buyers – village fixed effects

	Dependent variable: collection/working time (log)			
	First	Tot	Self	Wage
	(1)	(2)	(3)	(4)
Travel time (log)	0.211***			
	(0.024)			
Hours spent collecting (log)		−0.024	−0.760***	0.637***
		(0.101)	(0.221)	(0.213)
Households controls	yes	yes	yes	yes
Energy controls	yes	yes	yes	yes
Village controls	yes	yes	yes	yes
Village FE	yes	yes	yes	yes
Observations	5,315	5,315	5,315	5,315
F-stat first stage	76.35			

Notes: All estimations contain a constant. Standard errors in parentheses are clustered at the district level. ***p<0.01, **p<0.05, *p<0.1.

Buyers Results for buyers are presented in Table 11. In the case of buyers, we observe a positive impact also when looking at all labor market activities. A 10% increase in collection time increases the time spent on the labor market by 1.4%. When splitting between self and wage employment, we observe that wage employment is driving the result for the whole sample. The positive impact on wage employment is similar in magnitude to the one observed for non-buyers, yet in the case of buyers we do not observe any impact on self employment. A large increase in the price could push some buyers to reduce the quantities bought and increase the collection time. According to our theoretical model, distance from the nearest urban area should have a negative impact on collection, because of the decrease in price as one moves further out. Yet, this is a second order effect. The coefficient on distance is not statistically significant.

Also in the case of net buyers of fuelwood, the introduction of village level fixed effects highlights the basic results and eliminates the statistical significance of the result on wage employment, as shown in Table 12.

Table 11: Second stage buyers

	Dependent variable: working time (log)			
	(1)	(2)	(3)	(4)
All activities:				
Hours spent collecting (log)	0.205**	0.206**	0.159*	0.141*
	(0.081)	(0.082)	(0.086)	(0.083)
Distance to nearest town (log)				0.049
				(0.041)
Self employment:				
Hours spent collecting (log)	0.050	0.076	0.061	−0.022
	(0.158)	(0.164)	(0.168)	(0.161)
Distance to nearest town (log)				0.030
				(0.080)
Wage employment:				
Hours spent collecting (log)	0.259*	0.243*	0.203	0.226
	(0.134)	(0.136)	(0.138)	(0.139)
Distance to nearest town (log)				0.045
				(0.068)
Households controls	no	yes	yes	yes
Energy controls	no	no	yes	yes
Village controls	no	no	no	yes
District FE	yes	yes	yes	yes
Observations	1,325	1,325	1,325	1,325

Notes: All estimations contain a constant. Standard errors in parentheses are clustered at the district level. ***p<0.01, **p<0.05, *p<0.1.

Table 12: Buyers – village fixed effects

	Dependent variable: collection/working time (log)			
	First	Tot	Self	Wage
	(1)	(2)	(3)	(4)
Travel time (log)	0.264***			
	(0.019)			
Hours spent collecting (log)		0.175**	0.162	0.189
		(0.078)	(0.187)	(0.151)
Households controls	yes	yes	yes	yes
Energy controls	yes	yes	yes	yes
Village controls	yes	yes	yes	yes
Village FE	yes	yes	yes	yes
Observations	1,325	1,325	1,325	1,325
F-stat first stage	203.00			

Notes: All estimations contain a constant. Standard errors in parentheses are clustered at the district level. ***p<0.01, **p<0.05, *p<0.1.

4.2.1 Identifying sellers

The results presented for non-buyers may be biased by the presence of households which are non-buyers but also non-sellers. In order to identify the net sellers we use data on 68,451 households from the 2005 National Sample Survey (NSS). These data are useful because they contain information on fuelwood consumption by households; information which is not contained in the IHDS data. After identifying a set of explanatory variables for fuelwood consumption which are available in both datasets, we proceed to estimate consumption of fuelwood by households in every district contained in our dataset. Running a separate estimation for each district allows us to capture district-specific differences such as climate, topography or a better availability of electrical connections. This estimation is performed using the following explanatory variables: household size, a dummy for whether the household's main occupation is agriculture, one for whether the household's religion is Hinduism, the total surface of land cultivated, whether the dwelling unit is owned or not, whether the household has a ration card, the percentage of the household above 15 years of age, and a set of dummies identifying whether the household uses fuelwood, electricity, dung, kerosene or LPG. Using the district-specific coefficients obtained from the regressions on the NSS data, we then proceed to estimate predicted consumption values for the households in our sample. We now assume that people who buy fuelwood, if they collect, they collect only the extra quantity needed in order to fulfill their fuelwood consumption needs. By taking the difference between their predicted consumption and the kg of fuelwood they bought and dividing it by the number of hours spent in collection we obtain an estimate of the quantity of fuelwood that they collect per hour. We then take the village average of collection per hour by net buyers. At this point, we can multiply the village collection rate by the hours spent in collection by non-buying households and subtract their predicted consumption. If the number obtained is bigger than zero, the household is classified as a net-seller. Figure 6 highlights how this procedure manages to eliminate from the non-buyers the people who are also non-sellers. The proportion of non-buyers and non-sellers seems to be relatively constant as we move away from towns.

Figure 6: Number of non-buyers and sellers as a function of the distance from the nearest town

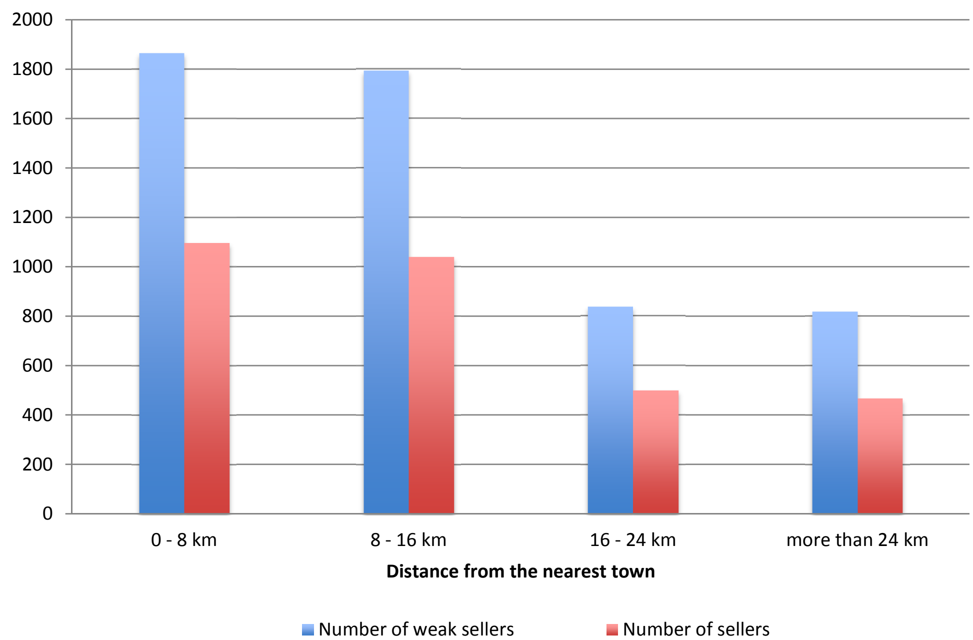


Figure 7: Number of sellers and buyers as a function of the distance from the nearest town

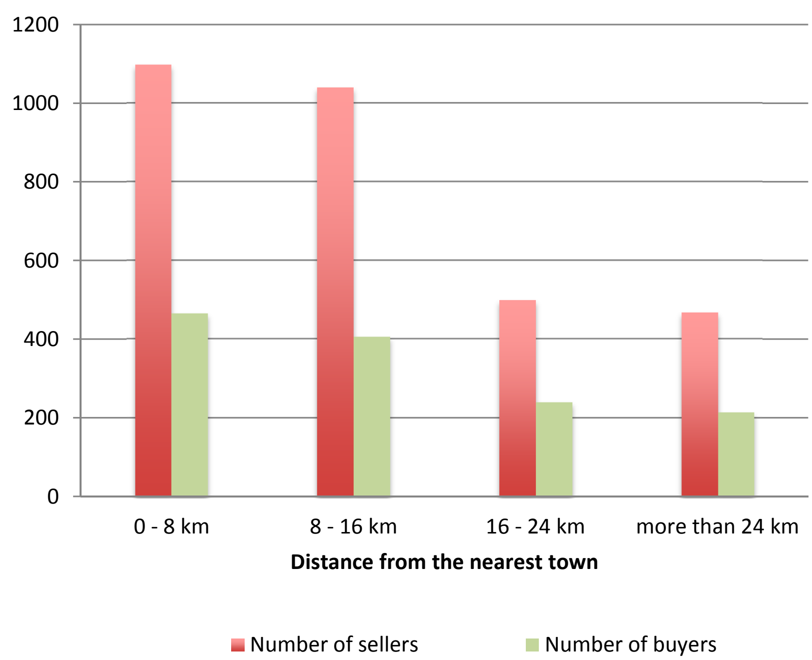


Figure 7 shows the evolution of the number of sellers and buyers as we move to villages located farther from a town. The number of sellers decreases by more than a half as we move away from an urban area, this result is aligned with our theoretical model: sellers tend to be located close to urban centers, where they can obtain the highest price and where the important market is located. The same pattern could already be observed for non-buyers, in Figure 6. As expected, buyers are a minority in rural areas, and the more remote the area the less people are buying fuelwood.

Table 13: Descriptive statistics sellers

Variable	**Mean**	**St. Dev.**	**Min**	**Max**
Sellers				
Share collecting resources	1.00	0.00	1.00	1.00
Hours per week in collection	3.61	3.24	0.10	28.00
Share working	0.98	0.15	0.00	1.00
Share of household in the labor market	0.74	0.27	0.00	1.00
Hours per week in the labor market	22.09	12.03	0.00	84.81
Hours per week in self-employment	8.94	10.51	0.00	63.17
Hours per week in wage activities	13.15	12.18	0.00	70.38
Travel time (min)	46.95	32.16	2.00	180
Household size	5.63	2.77	1.00	31.00
Share of Household >15 and < 65 years	67.29	21.44	16.67	100.00
Years of education of the head of household	3.57	4.12	0.00	15.00
Share of Women in the household	48.91	16.39	0.00	1.00
Hindu	0.88	0.33	0.00	1.00
Household income per cons unit (Rs)	12,395	18,573	56	718,750
Involved in Conflict	0.41	0.49	0.00	1.00
Electricity connection	0.68	0.47	0.00	1.00
Firewood	0.99	0.11	0.00	1.00
Crop residue	0.21	0.41	0.00	1.00
Kerosene	0.93	0.26	0.00	1.00
LPG	0.11	0.32	0.00	1.00
Households below the poverty line	0.23	0.42	0.00	1.00

Notes: We have 2,911 sellers.

Table 13 reports descriptive statistics for the household which we identified as net sellers of fuelwood. The characteristics of these households are very similar to the ones of the non-buyers, this is expected since the sellers are a large subgroup of the non-buyers. Yet, sellers spend slightly more time than non-buyers in collection and in self-employment. Sellers also appear to be slightly richer than non-buyers.

Figure 8 shows that the majority of fuelwood is sold in proximity to urban centers, more exactly up to roughly 30 kilometers from them. Figure 9 and Figure 10 illustrate that also the average quantities sold of fuelwood are larger closer to urban centers. Figure 9 fits a linear prediction to the average quantities sold, which clearly shows the negative relationship with the distance from town. Figure 10, instead, shows a scatter plot and a local polynomial estimation of the average quantity of fuelwood sold by each household. There is a clear pattern where household closer to cities sell on average larger amounts of fuelwood. When we get too close to the city the quantity decreases again and this may be due to the reduction in the availability of fuelwood in close proximity to cities.

Figure 8: Total quantity of fuelwood sold as a function of the distance from the nearest town

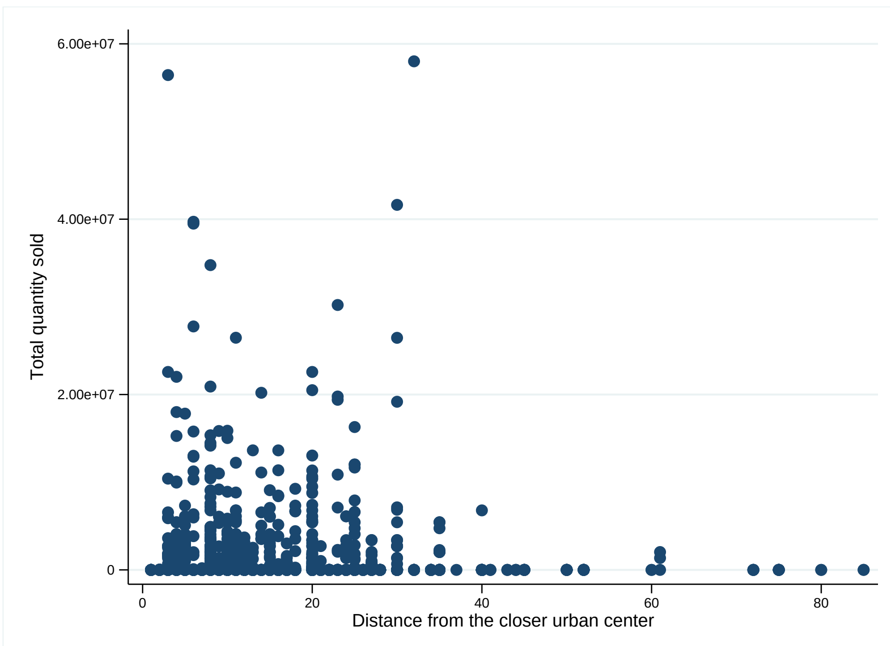


Table 14 reports labor market results for the new set of sellers. The selection procedure based on the NSS data eliminated 1,735 households which do not buy any fuelwood and do not sell any either. Column (1) shows results for the first stage, while columns (2), (3) and (4) outline second stage results for all activities, self and wage employment, respectively. The coefficient on travel time is equal to the one we obtained for non-buyers, while the coefficient on the distance from the closest town is larger in magnitude and now statistically significant at the 1% level. A 10% increase in the distance from the closest town decreases time spent in collection by 0.5%. Regarding the second stage, the results are similar in

Figure 9: Average quantity of fuelwood sold as a function of the distance from the nearest town with linear fitted values

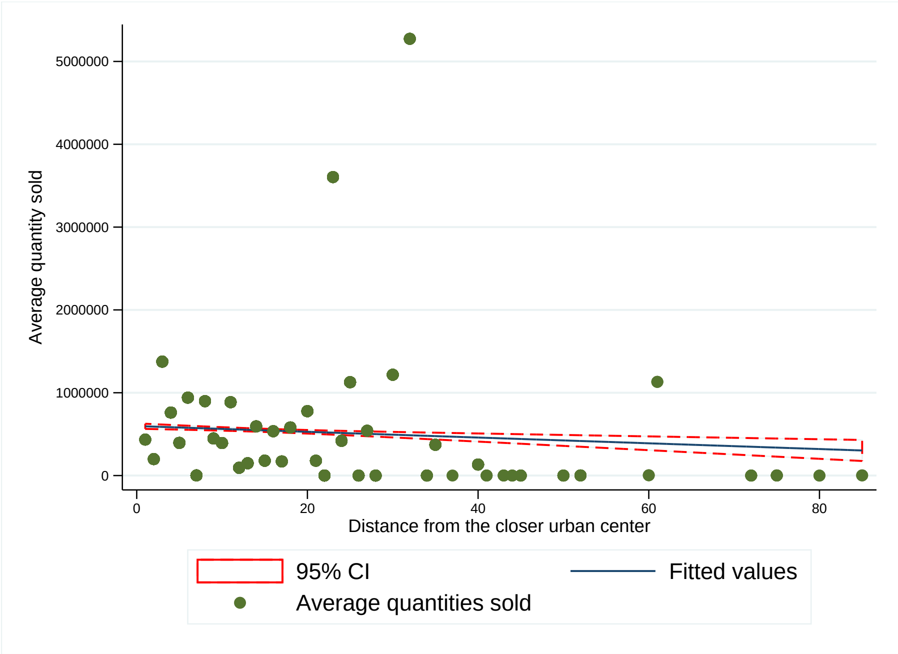


Figure 10: Average quantity of fuelwood sold as a function of the distance from the nearest town with non-linear fitted values

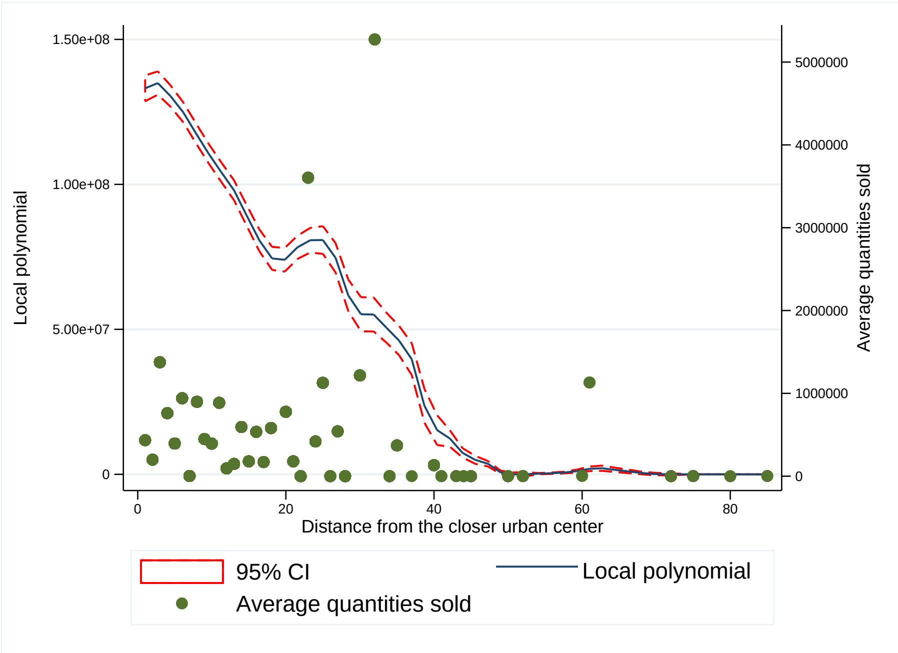


Table 14: Sellers - district fixed effects

	Dependent variable: collection/working time (log)			
	First	Tot	Self	Wage
	(1)	(2)	(3)	(4)
Travel time (log)	0.177***			
	(0.023)			
Hours spent collecting (log)		−0.001	−0.741**	0.648*
		(0.164)	(0.291)	(0.329)
Distance to nearest town (log)	−0.010	0.007	0.142**	−0.077
	(0.021)	(0.029)	(0.060)	(0.057)
Households controls	yes	yes	yes	yes
Energy controls	yes	yes	yes	yes
Village controls	yes	yes	yes	yes
District FE	yes	yes	yes	yes
Observations	2,911	2,911	2,911	2,911
F-stat first stage	56.39			

Notes: All estimations contain a constant. Standard errors in parentheses are clustered at the district level. ***p<0.01, **p<0.05, *p<0.1.

term of sign to the coefficients for the non-buyers, yet now they have a higher statistical significance and they are bigger in magnitude.

Table 15 reports results for a specification with village fixed effects for sellers. Also in this case, replacing district fixed effects with village fixed effects highlights the same mechanism as before. The statistical significance of the impact on wage employment decreases and, here as well, the statistical significance of the coefficient on self-employment increases significantly.

Table 15: Sellers - village fixed effects

	Dependent variable: collection/working time (log)			
	First	Tot	Self	Wage
	(1)	(2)	(3)	(4)
Travel time (log)	0.189^{***}			
	(0.029)			
Hours spent collecting (log)		-0.295	-0.989^{***}	0.409
		(0.181)	(0.367)	(0.369)
Households controls	yes	yes	yes	yes
Energy controls	yes	yes	yes	yes
Village controls	yes	yes	yes	yes
Village FE	yes	yes	yes	yes
Observations	2,911	2,911	2,911	2,911
F-stat first stage	43.21			

Notes: All estimations contain a constant. Standard errors in parentheses are clustered at the district level. ***p<0.01, **p<0.05, *p<0.1.

5 Robustness

We run a variety of robustness checks on the main specification. We start by analyzing elements which could violate the exclusion restriction and then move on to controlling for other potential confounding factors. The first robustness for the exclusion restriction was already presented above and consisted in replacing district with village fixed effects, in order to control for the eventual endogenity of placement of villages. A second test of the exclusion restriction consists in restricting the estimation to only the smaller villages in our sample, those below 5,000 inhabitants and those below 1,000 inhabitants. In Indian cities we observe spacial clusterings of people with similar professions, and therefore similar wage levels and socio-economic status. If this is the case, our instrument may not only capture the effect on collection decisions coming from the availability of forest, but also effects coming from the fact that similar people cluster in similar areas. In bigger villages we encounter a higher probability of observing settlement behaviors similar to those observed in cities. In smaller villages, instead, the probability of observing such a pattern decreases significantly. In smaller villages slightly richer people tend to settle closer to higher quality land.

Table 16: Robustness – small villages

	Dependent variable: collection/working time (log)			
	First	Tot	Self	Wage
	(1)	(2)	(3)	(4)
Villages with less than 5,000				
Travel time (log)	0.286***			
	(0.012)			
Hours spent collecting (log)		0.119**	−0.200**	0.323***
		(0.047)	(0.081)	(0.071)
Distance to nearest town (log)	0.008	0.016	0.150***	−0.056*
	(0.021)	(0.021)	(0.036)	(0.031)
Observations	8,615	8,615	8,615	8,615
F-stat first stage	558.82			
Villages with less than 1,000				
Travel time (log)	0.289***			
	(0.023)			
Hours spent collecting (log)		0.162	−0.175	0.259*
		(0.128)	(0.182)	(0.140)
Distance to nearest town (log)	−0.033	0.012	0.200*	−0.056
	(0.027)	(0.045)	(0.103)	(0.089)
Observations	2,764	2,764	2,764	2,764
F-stat first stage	155.87			
Households controls	yes	yes	yes	yes
Energy controls	yes	yes	yes	yes
Village controls	yes	yes	yes	yes
District FE	yes	yes	yes	yes

Notes: All estimations contain a constant. Standard errors in parentheses are clustered at the district level. ***p<0.01, **p<0.05, *p<0.1.

Table 16 shows results for running our main specification only on villages with less than 5,000 inhabitants and less than 1,000 inhabitants, respectively. The main results are left unchanged, suggesting that our instrument does not violate the exclusion restriction.

In Table 17 we add controls which could impact collection behavior. First, we add the number of cow and buffalo owned by the household, the total agricultural land owned and the total agricultural land rented or sharecropped by the household. Animal ownership may affect collection because the household will dispose of more dung, in the same way, ownership (or cultivation) of a more extended area may provide the household with a more important supply of crop residues. The results are robust to these controls. Second, we control for the interaction between wages and distance from the closer town. This interaction allows us to control for the fact that wages may be decreasing as we move away from cities and this may affect labor market decisions. Table 17 shows baseline results with the additional variables. Here again, the baseline results are not affected and seem to be robust to this additional controls.

We then proceed to exclude from the sample all households living either in the districts where India's ten biggest cities are located or in any of their neighboring districts. This test allows us to understand whether the effect observed is driven only by the biggest cities or if it is true for all urban centers. Results are presented in Table 18. Baseline results (all households) are robust to our baseline specification yet, it is interesting to notice that the differential effect on self employment for sellers disappears, so it seems that big cities are driving sales of fuelwood (and therefore deforestation).

In Table 19 we split the sample between the 2,313 households living below the poverty line and the 7,822 living above it. It could be the case the the poorest households are driving the results. Instead, we observe that it seems that household above the poverty line are driving this results. This is not surprising knowing, from Table 13, that only 23 percent of the sellers lives below the poverty line.

6 Concluding Remarks

This paper studies fuelwood markets by looking at the effect of reduced forest cover on time allocation by households. By disaggregating households into buyers and sellers, we find a clear difference in the behavior of the two groups as a function of access to resources and distance to nearby towns. We find that an increase in distance to forests induces sellers to reduce time spent in self-employment while buyers do not change their behavior significantly. This makes economic sense because with scarce forest resources, sellers substitute away from self-employment activities and invest more time in forest collection.

Table 17: Robustness – additional variables

	Dependent variable: collection/working time (log)			
	First	Tot	Self	Wage
	(1)	(2)	(3)	(4)
Additional variables (animal ownership and land owned and rented out)				
Travel time (log)	0.266***			
	(0.012)			
Hours spent collecting (log)		0.136***	−0.281***	0.389***
		(0.045)	(0.071)	(0.068)
Distance to nearest town (log)	0.018	0.011	0.074*	−0.025
	(0.023)	(0.022)	(0.043)	(0.040)
No of cows and buffalo owned	0.002	−0.038***	0.065***	−0.106***
	(0.005)	(0.009)	(0.015)	(0.019)
Total agricultural land owned (acres)	0.0001	−0.006**	0.077***	−0.084***
	(0.002)	(0.003)	(0.010)	(0.009)
Total agricultural land rented out or shared	0.001	−0.030**	−0.096***	0.059***
	(0.002)	(0.013)	(0.013)	(0.011)
Observations	6,735	6,735	6,735	6,735
F-stat first stage	475.11			
Additional variables (interaction wage with distance from town)				
Travel time (log)	0.274***			
	(0.012)			
Hours spent collecting (log)		0.119***	−0.166**	0.294***
		(0.040)	(0.065)	(0.063)
Distance to nearest town (log)	0.123	−0.142	0.605	−0.585**
	(0.192)	(0.190)	(0.401)	(0.269)
Unskilled wage (log)	0.027	−0.212	0.213	−0.333*
	(0.135)	(0.137)	(0.320)	(0.175)
*Distance to nearest town (log) * Unskilled wage (log)*	−0.031	0.040	−0.127	0.140**
	(0.047)	(0.050)	(0.102)	(0.068)
Observations	10,169	10,169	10,169	10,169
F-stat first stage	558.43			
Households controls	yes	yes	yes	yes
Energy controls	yes	yes	yes	yes
Village controls	yes	yes	yes	yes
District FE	yes	yes	yes	yes

Notes: All estimations contain a constant. Standard errors in parentheses are clustered at the district level. ***p<0.01, **p<0.05, *p<0.1.

Table 18: Robustness – without 10 biggest cities and their area of influence

	Dependent variable: collection/working time (log)			
	First	Tot	Self	Wage
	(1)	(2)	(3)	(4)
All households				
Travel time (log)	0.266***			
	(0.012)			
Hours spent collecting (log)		0.116**	−0.197***	0.327***
		(0.047)	(0.071)	(0.069)
Distance to nearest town (log)	0.003	0.016	0.113***	−0.034
	(0.022)	(0.019)	(0.038)	(0.033)
Observations	8,779	8,779	8,779	8,779
F-stat first stage	493.48			
Buyers				
Travel time (log)	0.256***			
	(0.015)			
Hours spent collecting (log)		0.135	−0.234	0.379***
		(0.089)	(0.147)	(0.142)
Distance to nearest town (log)	0.047	0.046	0.026	0.073
	(0.043)	(0.040)	(0.085)	(0.072)
Observations	1,183	1,183	1,183	1,183
F-stat first stage	277.71			
Sellers				
Travel time (log)	0.190***			
	(0.024)			
Hours spent collecting (log)		0.085	−0.670**	0.730**
		(0.155)	(0.266)	(0.305)
Distance to nearest town (log)	−0.001	−0.004	0.128**	−0.069
	(0.023)	(0.030)	(0.062)	(0.061)
Observations	2,725	2,725	2,725	2,725
F-stat first stage	61.06			
Households controls	yes	yes	yes	yes
Energy controls	yes	yes	yes	yes
Village controls	yes	yes	yes	yes
District FE	yes	yes	yes	yes

Notes: All estimations contain a constant. Standard errors in parentheses are clustered at the district level. ***p<0.01, **p<0.05, *p<0.1.

Table 19: Robustness – above and below the poverty line

	Dependent variable: collection/working time (log)			
	First	Tot	Self	Wage
	(1)	(2)	(3)	(4)
Households above the poverty line				
Travel time (log)	0.272***			
	(0.012)			
Hours spent collecting (log)		0.121***	−0.139**	0.301***
		(0.045)	(0.067)	(0.069)
Distance to nearest town (log)	0.014	0.004	0.080*	−0.036
	(0.023)	(0.022)	(0.043)	(0.036)
Observations	7,861	7,861	7,861	7,861
F-stat first stage	492.44			
Households below the poverty line				
Travel time (log)	0.299***			
	(0.020)			
Hours spent collecting (log)		0.112	−0.217*	0.167
		(0.094)	(0.125)	(0.138)
Distance to nearest town (log)	−0.021	0.021	0.209***	−0.088*
	(0.030)	(0.034)	(0.050)	(0.046)
Observations	2,304	2,304	2,304	2,304
F-stat first stage	221.10			
Households controls	yes	yes	yes	yes
Energy controls	yes	yes	yes	yes
Village controls	yes	yes	yes	yes
District FE	yes	yes	yes	yes

Notes: All estimations contain a constant. Standard errors in parentheses are clustered at the district level. ***p<0.01, **p<0.05, *p<0.1.

Both groups spend more time collecting when access to forests is costlier.

Both buyers and sellers respond differently to their location relative to the nearest town. Buyers are less responsive overall since they only participate in the local market, while sellers decrease their collection effort and increase time spent in self-employment further away from town. By matching two different datasets we can clearly identify the households that are net sellers of fuelwood. The number of sellers increases as we go get closer to town while the number of buyers shows no such trend. The excess supply of fuelwood from each location decreases with distance from town. Given that fuelwood markets are primarily local, this suggests that demand from nearby urban centers is an important driver of fuelwood collection in the hinterland.

These findings suggest that an important factor behind deforestation induced by fuelwood collection may be the demand for energy in towns and cities, and not from household consumption in rural areas. To that extent, policies that aim to combat deforestation and reduce collection need to consider energy choices in urban areas, especially in the informal sector. For example, one way to reduce forest collection may be to reduce the demand for fuelwood in nearby urban areas through subsidies for alternative fuels and by introducing energy-efficient appliances such as stoves. Future work can focus on estimating fuelwood demand in the urban sector and match it with supply from rural areas in close proximity.

References

Amacher, G., Hyde, W., and Kanel, K. (1996). Household Fuelwood Demand and Supply in Nepal's Tarai and Mid-Hills: Choice between Cash Outlays and Labor Opportunity. *World Development*, 24(11):1725–1736.

Baland, J.-M., Bardhan, P., Das, S., Mookherjee, D., and Sarkar, R. (2010). The Environmental Impact of Poverty: Evidence from Firewood Collection in Rural Nepal. *Economic Development and Cultural Change*, 59(1):23–61.

Bandyopadhyay, S., Shyamsundar, P., and Baccini, A. (2011). Forests, Biomass Use and Poverty in Malawi. *Ecological Economics*, 70(12):2461–2471.

Cooke, P. (1998a). The Effect of Environmental Good Scarcity on Own-Farm Labor Allocation: the Case of Agricultural Households in Rural Nepal. *Environment and Development Economics*, 3(04):443–469.

Cooke, P. (1998b). Intrahousehold Labor Allocation Responses to Environmental Good

Scarcity: A Case Study from the Hills of Nepal. *Economic Development and Cultural Change*, 46(4):807–30.

FAO (2010). Global Forest Resource Assessment - Main Report. FAO Forestry Paper 163.

Foster, A. and Rosenzweig, M. (2003). Economic Growth and the Rise of Forests. *The Quarterly Journal of Economics*, 118(2):601–637.

Ilahi, N. and Grimard, F. (2000). Public Infrastructure and Private Costs: Water Supply and Time Allocation of Women in Rural Pakistan. *Economic Development and Cultural Change*, 49(1):45–75.

Koolwal, G. and van de Walle, D. (2013). Access to Water, Women's Work, and Child Outcomes. *Economic Development and Cultural Change*, 61(2):369 – 405.

Kumar, S. and Hotchkiss, D. (1988). Consequences of Deforestation for Women's Time Allocation, Agricultural Production, and Nutrition in Hill Areas of Nepal:. Research reports 69, International Food Policy Research Institute (IFPRI).

Lokshin, M. and Yemtsov, R. (2005). Has Rural Infrastructure Rehabilitation in Georgia Helped the Poor? *World Bank Economic Review*, 19(2):311–333.

National Sample Survey Office, Ministry of Statistics & Programme Implementation, G. o. I. (2010). Migration in india 2007-2008. NSS report 533.

Tiwari, P. (2007). *India Infrastructure Report 2007: Rural Infrastructure*, chapter Rural Housing in India, pages 247–264. Oxford University Press.

Table A.1: Forest cover by state

	2000			2004			Δ		
State	Dense	Open	Total	Dense	Open	Total	Dense	Open	Total
Andaman & Nicobar Islands	0.80	0.04	0.84	0.73	0.08	0.80	-0.07	0.03	-0.04
Andhra Pradesh	0.09	0.07	0.16	0.09	0.07	0.16	-0.005	0.004	-0.001
Arunachal Pradesh	0.54	0.18	0.72	0.57	0.22	0.80	0.04	0.04	0.07
Assam	0.13	0.11	0.24	0.10	0.15	0.26	-0.03	0.04	0.01
Bihar	0.04	0.02	0.06	0.03	0.03	0.06	-0.003	0.001	-0.001
Chandigarh	0.04	0.03	0.07	0.08	0.05	0.13	0.04	0.02	0.06
Chhattisgarh	0.28	0.14	0.42	0.29	0.13	0.41	0.006	-0.01	-0.004
Dadra and Nagar Haveli	0.31	0.14	0.45	0.26	0.18	0.45	-0.04	0.05	0.004
Daman & Diu	0.01	0.04	0.05	0.02	0.06	0.08	0.004	0.02	0.02
Delhi	0.03	0.05	0.07	0.04	0.08	0.12	0.01	0.03	0.04
Goa	0.16	0.13	0.29	0.15	0.14	0.29	-0.01	0.01	-0.0002
Gujarat	0.04	0.03	0.08	0.03	0.04	0.07	-0.01	0.01	-0.002
Haryana	0.03	0.01	0.04	0.01	0.02	0.04	-0.01	0.01	-0.004
Himachal Pradesh	0.19	0.07	0.26	0.16	0.10	0.26	-0.03	0.03	0.0002
Jammu & Kashmir	0.06	0.04	0.09	0.05	0.05	0.09	-0.01	0.01	-0.0004
Jharkhand	0.16	0.17	0.34	0.14	0.20	0.34	-0.02	0.03	0.01
Karnataka	0.14	0.06	0.19	0.11	0.07	0.18	-0.02	0.01	-0.01
Kerala	0.30	0.10	0.40	0.25	0.15	0.40	-0.05	0.05	0.001
Lakshadweep	0.86	0.00	0.86	0.47	0.31	0.78	-0.40	0.31	-0.08
Madhya Pradesh	0.14	0.11	0.25	0.13	0.11	0.25	-0.01	0.01	-0.004
Maharashtra	0.10	0.05	0.15	0.09	0.06	0.15	-0.01	0.01	-0.00002
Manipur	0.26	0.50	0.76	0.29	0.48	0.76	0.03	-0.03	0.01
Meghalaya	0.25	0.44	0.69	0.32	0.44	0.76	0.06	-0.003	0.06
Mizoram	0.42	0.41	0.83	0.30	0.59	0.89	-0.12	0.18	0.06
Nagaland	0.32	0.48	0.80	0.35	0.47	0.83	0.03	-0.004	0.02
Orissa	0.18	0.13	0.31	0.18	0.13	0.31	0.001	-0.004	-0.003
Pondicherry	0.07	0.003	0.07	0.03	0.05	0.09	-0.04	0.05	0.012
Punjab	0.03	0.02	0.05	0.01	0.02	0.03	-0.02	-0.001	-0.02
Rajasthan	0.02	0.03	0.05	0.01	0.03	0.05	-0.005	0.004	-0.001
Sikkim	0.34	0.11	0.45	0.34	0.12	0.46	0.003	0.01	0.01
Tamilnadu	0.10	0.07	0.16	0.10	0.08	0.18	-0.0001	0.01	0.01
Tripura	0.33	0.34	0.67	0.48	0.30	0.78	0.15	-0.04	0.10
Uttar Pradesh	0.04	0.02	0.05	0.02	0.03	0.06	-0.01	0.01	0.002
Uttaranchal	0.36	0.09	0.45	0.34	0.11	0.46	-0.01	0.02	0.01
West Bengal	0.07	0.05	0.12	0.07	0.07	0.14	-0.003	0.02	0.02
India	0.13	0.08	0.20	0.12	0.09	0.21	-0.01	0.01	0.003

Table A.2: First stage

	Dependent variable collection time			
	(1)	(2)	(3)	(4)
Travel time (log)	0.286***	0.282***	0.274***	0.274***
	(0.011)	(0.011)	(0.012)	(0.012)
Household size		0.004	0.006**	0.006**
		(0.003)	(0.003)	(0.003)
Share of household 15-65 years		−0.001**	−0.001*	−0.001*
		(0.000)	(0.000)	(0.000)
Years of schooling of the head of household		−0.005	−0.004	−0.005
		(0.003)	(0.003)	(0.003)
Years of schooling of the head squared		−0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
Hindu		−0.031	−0.035	−0.034
		(0.033)	(0.033)	(0.033)
Household income (log)		−0.017**	−0.006	−0.005
		(0.008)	(0.008)	(0.008)
Involved in conflict		0.000	0.001	−0.000
		(0.027)	(0.026)	(0.026)
Electricity use			−0.033**	−0.034**
			(0.016)	(0.016)
fuelwood use			0.044*	0.042*
			(0.024)	(0.026)
Crop residues use			0.083***	0.082***
			(0.029)	(0.029)
Kerosene use			−0.052	−0.052
			(0.037)	(0.038)
LPG use			−0.118***	−0.119***
			(0.025)	(0.025)
Employment program in village				0.051
				(0.033)
Distance to nearest town (log)				0.004
				(0.021)
Village population btw 1001 and 5000				−0.036
				(0.034)
Village population above 5000				−0.024
				(0.044)
Unskilled average wage (log)				−0.048
				(0.048)
Observations	10,169	10,169	10,169	10,169
F-stat first stage	647.34	604.02	556.82	563.18

Notes: All estimations contain a constant. Standard errors in parentheses are clustered at the district level. ***p<0.01, **p<0.05, *p<0.1.

Table A.3: Full sample - village fixed effects

	Dependent variable: collection/working time (log)			
	First	Tot	Self	Wage
	(1)	(2)	(3)	(4)
Travel time (log)	0.273***			
	(0.012)			
Hours spent collecting (log)		0.127***	−0.182**	0.298***
		(0.043)	(0.074)	(0.067)
Households controls	yes	yes	yes	yes
Energy controls	yes	yes	yes	yes
Village controls	yes	yes	yes	yes
Village FE	yes	yes	yes	yes
Observations	10,169	10,169	10,169	10,169
F-stat first stage	538.63			

Notes: All estimations contain a constant. Standard errors in parentheses are clustered at the district level. ***p<0.01, **p<0.05, *p<0.1.

Figure B.1: Distribution of village size as a function of the distance from the nearest town

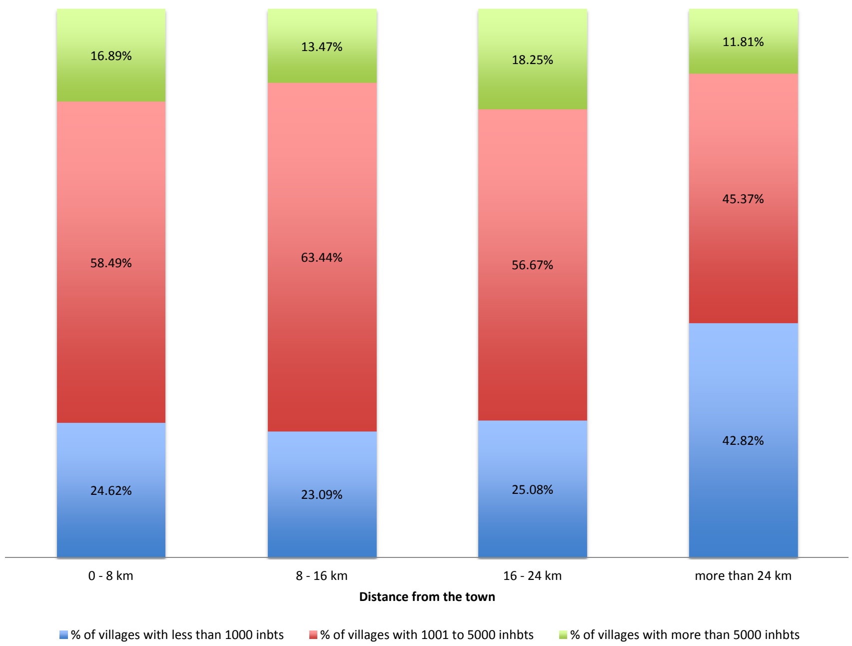


Figure B.2: Average quantity of fuelwood sold in small villages as a function of the distance from the nearest town

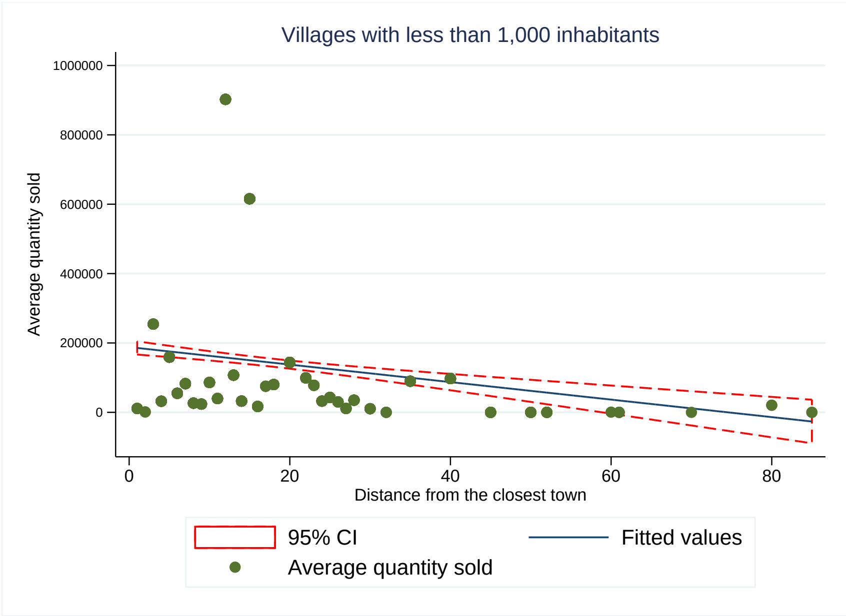


Figure B.3: Average quantity of fuelwood sold in medium villages as a function of the distance from the nearest town

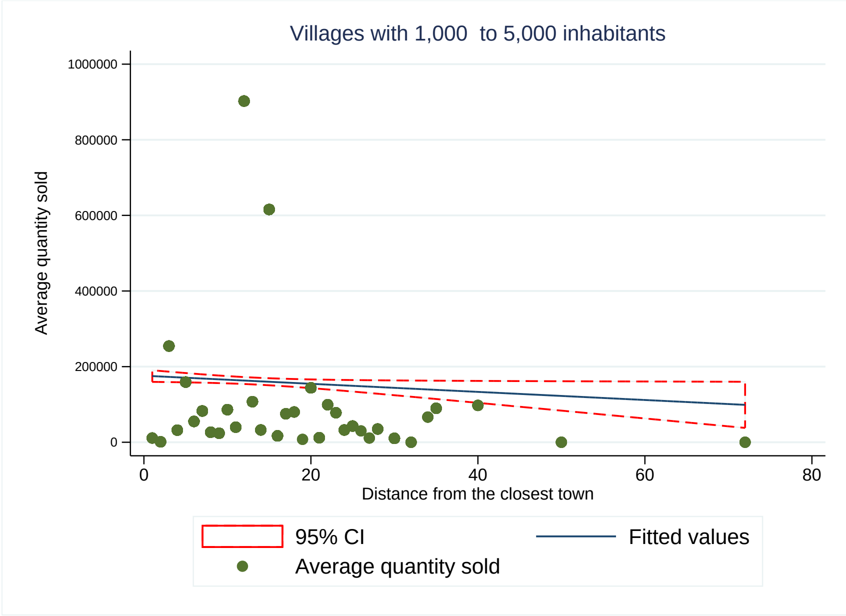


Figure B.4: Average quantity of fuelwood sold in big villages as a function of the distance from the nearest town

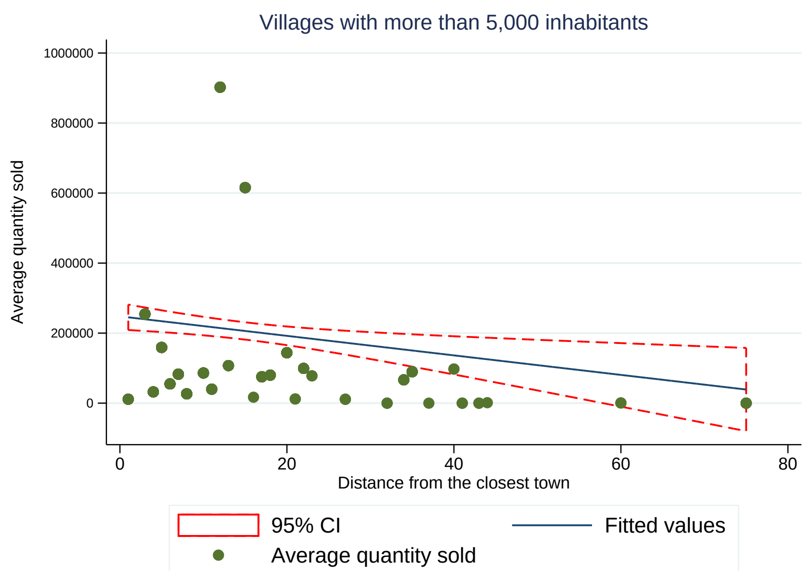


Figure B.5: Total quantity of fuelwood sold in small villages as a function of the distance from the nearest town

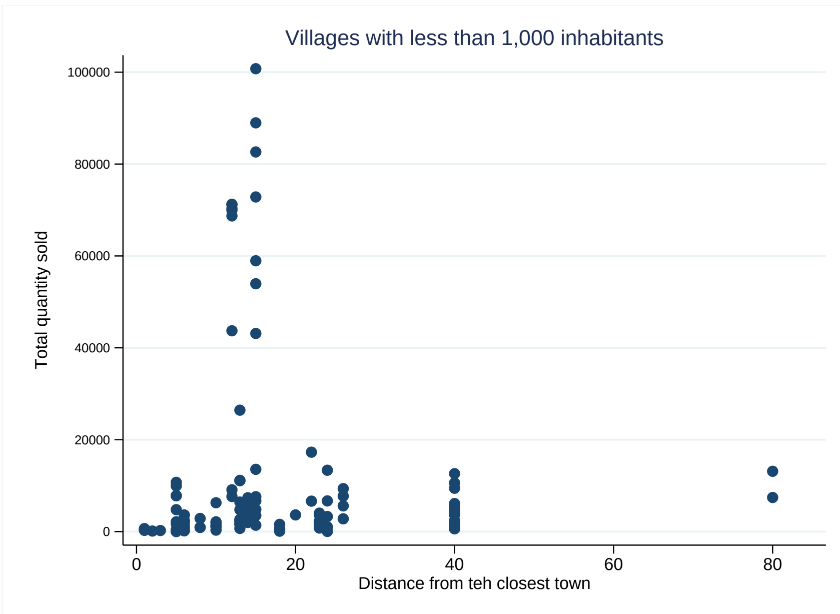


Figure B.6: Total quantity of fuelwood sold in medium villages as a function of the distance from the nearest town

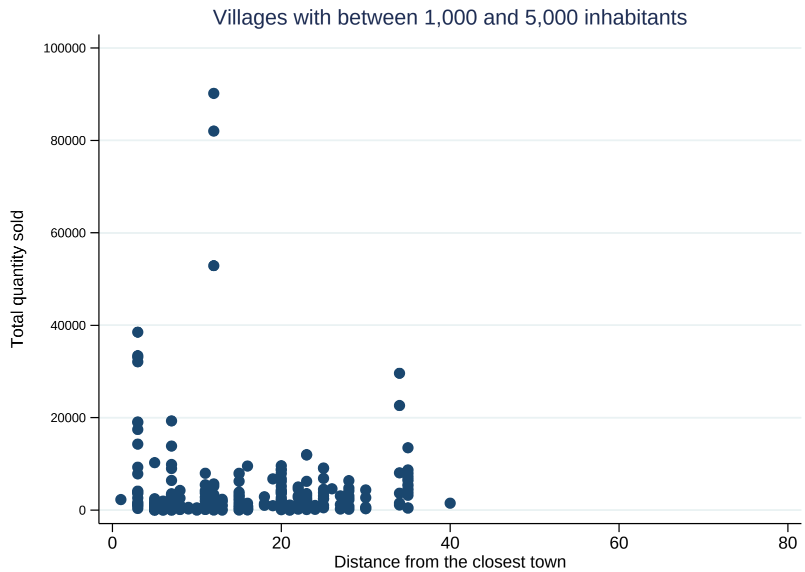


Figure B.7: Total quantity of fuelwood sold in big villages as a function of the distance from the nearest town