Far Away from the Forest? Fuelwood Collection and Time Allocation in Rural India[†]

Ujjayant Chakravorty [‡] Martino Pelli[§] Anna Risch[¶]

November 2014

Preliminary, please do not cite.

Abstract

We study the effect of reduced forest cover on household time allocation in rural India. We find that costlier access to forests increases the time households spend in collection and in wage-earning occupations. We instrument local forest cover 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 (because of a reduction in forest cover and in its density) and this may affect labor market decisions. By partitioning the sample into households who buy fuelwood from those who do not, we can see a clear difference in the labor market responses of the two groups. Higher travel times induce fuelwood sellers to reduce the time invested in self-employment in order to increase the time spent in collection and profit from higher prices. Buyers also collect more, but do not decrease self-employment activities. The behavior of these two groups is also different as a function of the distance of their village from the nearest town. Farther from the town, sellers reduce their collection effort, because the price they get is likely to be lower in villages away from urban market. However, buyers exhibit no such pattern in their behavior. The main contribution of the paper is in disentangling fuelwood markets into those who buy and those who sell. The implication is that fuelwood collection is likely driven not only by rural household demand but especially 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.

JEL classification: O12, O18, Q48

Keywords: Labor Markets, Forest Policy, Rural Development, Energy and Development, Fuelwood Markets

---

[†]We would like to thank seminar participants at the World Bank, the University of Michigan, Tufts University, the Chinese Academy of Sciences, the Montreal Workshop in Environmental and Resource Economics, the 9^{th} IZA/World Bank conference on Employment and Development, the World Congress of Resource and Environment Economists and the Canadian Study Group in Environmental and Resource Economics.

[‡]Department of Economics, Tufts University, 114A Braker Hall, 8 Upper Campus Rd., Medford, MA 02155-6722, USA. Email: Ujjayant.Chakravorty@tufts.edu

[§]Department of Economics, Université de Sherbrooke, K1-4097, Sherbrooke, QC, J1K 2R1, Canada. Email: Martino.Pelli@usherbrooke.ca

[¶]Department of Economics, University of Savoie, Annecy, France. Email: Anna.risch@univ-savoie.fr

1 Introduction

A large share of the population in developing countries relies on the environment for their basic needs such as food and energy (UNDP, 2011). Men and especially women spend many hours a day collecting fuelwood and other forest resources for their basic survival. Both poor and better-off households engage in this activity, although resource collection is especially strong among the poor who do not earn enough to buy all their goods and services from the market. However, they may participate as sellers of food and energy resources when these resources become scarce. Studies have shown that these environmental resources represent an important part of the income of rural households (Cavendish, 2000; Kamanga et al., 2009; Chakravorty and Gunatileke, 2003). Thus, understanding whether and how environmental degradation affects household labor market behavior is important in order to determine its impact on economic growth. The literature has mostly focused on the reverse relation, i.e. the impact of human activities on environmental degradation (Burgess et al., 2012; Cropper and Griffiths, 1994; Foster and Rosenzweig, 2003). In this paper, we study the impact of a reduction in forest cover on participation in the labor market in rural India.

Our objective is to study whether an increase in the time dedicated to resource collection has an impact on labor supply. Households adapt to fuel scarcity by adjusting fuelwood consumption, using substitutes or as is often the case, investing longer hours in collection. The extra time dedicated to resource collection affects participation in other activities, such as leisure or labor supply. Therefore, costlier access to forest resources, measured by the time spent collecting fuel, may lead to less time for productive activities, especially for women. Another hypothesis tested in this paper alongside labor market reactions is whether urban areas are mainly responsible for deforestation in India. According to the FAO over 50% of urban residents uses fuelwood as a source of energy, for this reason we claim that cities are the most active markets for fuelwood and they attract a large share of the fuelwood collected in the countryside. The identification of local fuelwood markets allows us to go one step farther than Foster and Rosenzweig (2003). Their paper studies the existence of an Environmental Kuznets Curve for forest in India, yet it fails to explain why there is no relationship between local demand for forest products and local household incomes.

Globally, more than 1.6 billion people rely in varying degrees on forests for their livelihood. Our study focuses on India, which is the tenth largest country in the world in terms of forest coverage with about 68 million hectares, roughly 20.8% of its area (FAO, 2010). Forests represent an important resource for people in India with about 200 million people relying on them for livelihood, according to the Ministry of Environment and Forest. About a quarter of the population using fuelwood gets it directly from the forest. India is the largest consumer of fuelwood in the world (Forest Survey of India report, 2011), which supplies about 40% of the country's energy needs. Current consumption is about five times higher than what can be sustainably removed from forests. An estimated 41% of India's forest cover has been degraded in the past decade - many areas which used to be considered *dense forest* are now considered *open forest*.[1] Pressure on India's forests comes from many sources, particularly the increase in the population from 390 million in 1950 to a billion in 2001 and the consequent over-utilization of resources. The per capita availability of forests went from roughly 0.07 ha per capita – already among the lowest in the world in 1990 to 0.05 ha per capita in 2011.[2] Forests are unevenly distributed in the country: only 6 out of 35 states account for 50% of the forest area, whereas 8 other states supply less than 0.05% of the forest area (for more details see Table A.1 in the Appendix).

Most previous studies on deforestation focus on its global impacts, greenhouse gas emissions (a fifth of which are generated by deforestation) and the reduction in biodiversity through the extinction of many species (Burgess et al., 2012; Cropper and Griffiths, 1994). One aspect of deforestation which is often overlooked concerns its impact on individuals through a decrease in the availability of forest resources, especially fuelwood. When households lose access to forest resources, they reduce consumption and spend more time in collection (Cooke, 1998b). Resource collection is predominantly a female activity (Kumar and Hotchkiss, 1988; Cooke, 1998a; Bandyopadhyay et al., 2011) and is carried out by women belonging to both poor as well as wealthier households (Baland et al., 2010). However, women are not the only members in the household involved in the collection of environmental goods such as fuel and water. Children are often active participants. School attendance may be negatively affected by the scarcity of natural resources and the resulting increase in the hours devoted to collection (Wagura Ndiritu and Nyangena, 2010). Nankhuni and Findeis (2003) show that children from the most environmentally degraded districts of central and southern Malawi are less likely to attend school.

The hypothesis tested in this paper is whether and how the decision to collect fuel – which depends on its scarcity – affects the household's decision of participation to the labor market. However, the decision to collect resources may be endogenous - there may be factors motivating both decisions, how much time to invest in collection and and how much in the labor market. To avoid this problem, we use an instrumental variable approach to isolate the variation in the time spent collecting forest products coming from a

[1] For an area to be classified as *dense forest* more than 40% of it must be covered by vegetation.

[2] Source: World Bank Development Indicators.

change in resource availability. The decrease in the availability of resources, in this case deforestation, is negatively correlated with the time needed to reach the resource, i.e. the forest. Therefore, we instrument the time invested in collection with the travel 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 has to be invested in collection and this may affect labor market decisions. We argue that in rural India, because of generally low household mobility and an inactive real estate market, household location may be considered exogenous to the forest boundary. Location may have been a factor in the decision to settle several generations ago, but with the gradual depletion of the forest cover over time, members of the household increasingly walk large distances to collect resources.

We examine the effect of longer travel times on the hours spent in resource collection. We further disentangle the data to check how costlier access to collection sites impacts household decisions to engage in wage-earning and non-wage activities such as the family farm. Our results suggest that resource scarcity leads households to spend more time collecting forest products - an increase of 10% in the distance from the collection location increases the time dedicated to it by 2.6%. this increase is mainly due to the fact that not only the forest cover is reducing but it is also becoming more scarce and therefore it takes more time to gather the same quantity of fuelwood. A 10% increase in the time spent in collection translates into an increase in the time spent in the labor market by 1.1%. When considering the whole sample, it seems that deforestation does not affect time spent in self-employment.

In order to gather a more precise understanding of the mechanisms at work, we split the sample between net buyers and net sellers of fuelwood. As predicted by a simple theoretical model, we highlight a clear difference in behavior between the two groups. In response to a decrease in the availability of fuelwood, sellers decrease the time invested in self-employment and increase the time spent in collection, possibly to profit from the higher prices. For them, a 10% increase in the distance from the collection location translates into a decrease in the time spent in self-employment by 0.7%. This effect becomes muted as they move away from the nearest town. Buyers of fuelwood, however, respond to a decrease in availability by *increasing* the time spent in collection (by 2.5%) and increasing the time spent in wage activities (by 6.5%). The shift to more wage-earning occupations may be explained by the need to cope with the increase in the price of energy due to lower access or by the fact that areas with a lower forest cover may be characterized by more agricultural activity and therefore more opportunities to be involved in wage employment.

The main contribution of our paper is to show the clear difference in buyer and seller behavior in their labor market response to reduced access to forests. The implication is that fuelwood collection may be driven not only by demand in rural households, but especially by demand from nearby urban centers. Empirical evidence shows that the price of fuelwood declines away from cities, and hence it affects those who sell and those who buy, differently. Sellers have less incentive to collect farther away, while buyers do not exhibit a significant change in their behavior. Similarly, given the same location, both buyers and sellers collect more in response to resource scarcity and increase their participation in wage-earning jobs (they need to earn more to buy more expensive fuelwood). These results suggest the forest policy ought to take into account who collects and for what purpose - whether for household consumption or for supplying to the market.

The literature on the impact of deforestation on individual decision-making is sparse. A few 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 and purchasing fuel are highly responsive to an increase in fuelwood prices and labor opportunities. These households rapidly switch from purchasing fuelwood to using household time – originally dedicated to labor market activities – they substitute purchased fuelwood with collected fuelwood. In contrast, collecting households do not react with the same speed to a change in fuelwood price. Moreover, Kumar and Hotchkiss (1988) show the negative impact of deforestation on women's farm labor input.

Other studies have focused on water collection. Ilahi and Grimard (2000) use simultaneous equations to 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. However, results diverge in the literature. Lokshin and Yemtsov (2005), using double differences, show 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, water has no substitute and demand is likely to be inelastic. Therefore, the behavior of households responding to the scarcity of water or scarcity of natural resources (such as fuelwood) may differ. However, these papers show that collection activities may not necessarily be linked to labor market supply and can have an impact only on leisure.

Section 2 develops a simple model of a representative 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.

2 A Simple Model of fuelwood Collection by Households

In this section, we model the choice of a representative household that allocates time to collect fuelwood either for domestic consumption or for sale. We assume for now that all households are alike, but later we discuss the implications of this model when households differ in terms of their physical location, labor endowments and reservation wage. 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.[3] Villages are small relative to towns hence individual households 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 d. Then the price in a village x kilometers away from the town can be written as $p - dx$, assuming linearity of transport costs. The price of fuelwood declines farther from the town.

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 the household is given by $U(q_f + \theta q_k)$ where $U(\cdot)$ 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. 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 will be a value smaller than one. Household-specific characteristics such as income or size may affect the shape of the utility function, but we consider that later. Each household is endowed with $\bar{t}$ units of time and the reservation wage of the household is given by $\bar{w}$. Later, we allow for heterogeneity in wages across households due to their different characteristics - more educated households may earn a higher wage. The household allocates time between collecting fuelwood and working for wages so that

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

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

where t_c is the time spent collecting fuelwood and t_w is time spent in wage labor.[4]

Let f be the volume of fuelwood collected per unit time. This includes the time spent traveling to the forest site and returning home. 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 residual fuelwood in the urban market at the given price $p - dx$. The price of the alternative fuel (e.g., kerosene) is given by p_k. The maximization problem of the household can then be written as

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

subject to (1) and $q_c = f t_c$. 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

$$L = U(q_f + \theta q_k) + \bar{w} t_w + (p - dx)(q_c - q_f) - p_k q_k + \lambda(\bar{t} - t_w - t_c). \tag{3}$$

which yields the first order conditions

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

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

Note that if the price of fuelwood in the village $p - dx$ 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 $U'(\cdot) = \frac{p_k}{\theta}$ 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 $\theta(p - dx) = p_k$. If kerosene is too expensive, the household will use only fuelwood if the latter is cheaper, or $U'(\cdot) = p - dx < p_k$. The remaining necessary conditions are

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

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

From (6), if the household collects then it must be the case that $(p - dx)f = \lambda$, that

[4] Here we abstain from considering household size.

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 bigger 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 household. If it is remote relative to the nearest town where the fuelwood is sold, households face a lower price for fuelwood. 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 relationship is shown in Figure 1. The top panel shows that the price of fuelwood falls with distance from the nearest town. We also introduced the reservation wage of a typical household shown by the horizontal wage line. This can be interpreted as the shadow price of its time. Households for which the price of fuelwood is higher than their reservation wage collect to sell fuelwood. Those for which the price of fuelwood is lower than their reservation wage, find more profitable to work in alternative occupations. Finally, consider a region with a lower endowment of forest cover (bottom panel). A decrease in the forest stock generates an increase in the price of fuelwood because of increased scarcity. Now a household may collect even if it is located farther from the city. *Ceteris paribus*, a lower stock of forest may increase collection time as well.

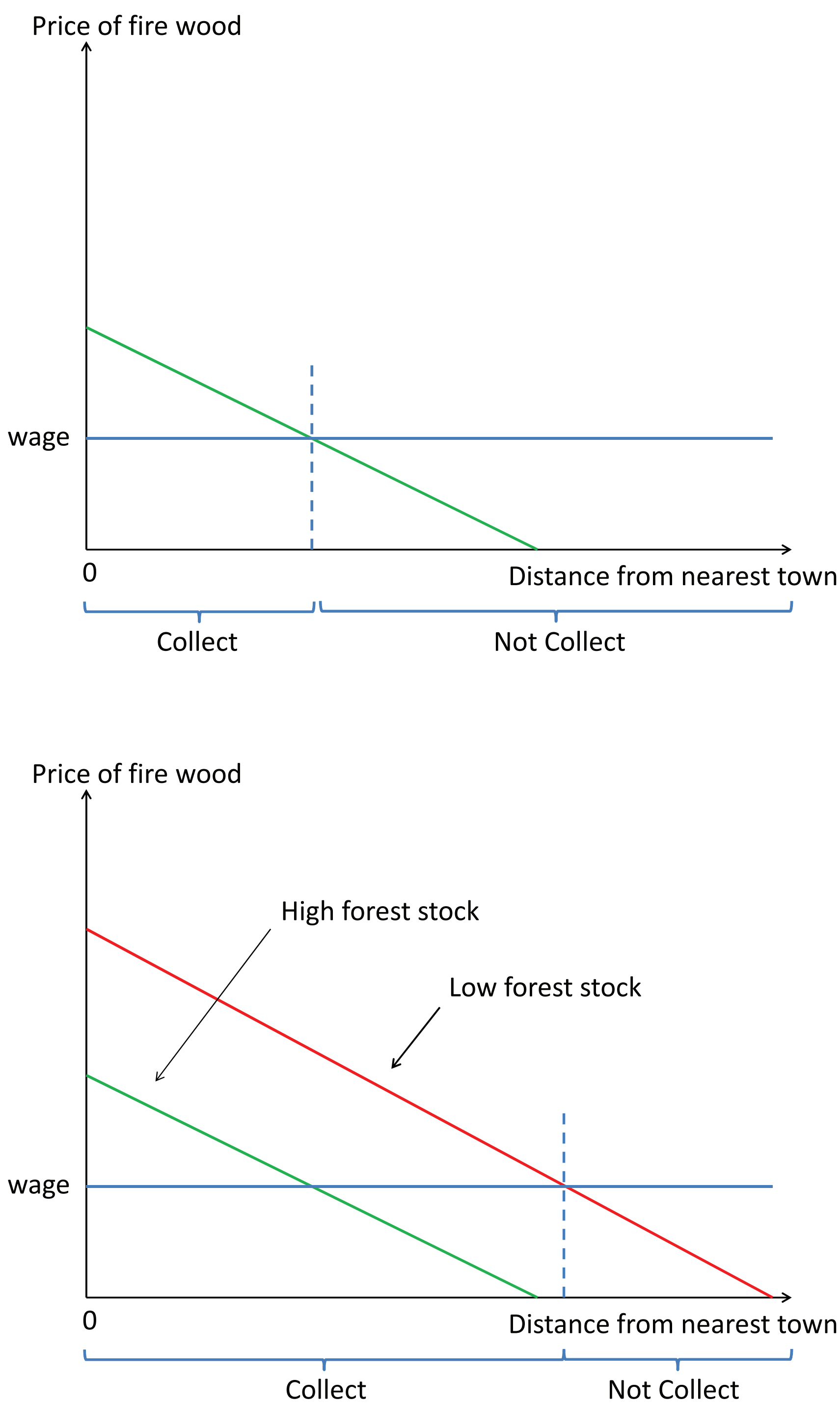
Although we do not explicitly model heterogeneity among households here, it is clear that not only will households differ in terms of their location and travel costs, but also their time endowment and reservation wage. For example, a household with more skilled labor may enjoy a higher wage, in which 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.*

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



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 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. Data were collected between 2004 and 2005 and contain 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 households living in rural India.[5]

Table 1 reports descriptive statistics for the variables employed in the estimation. 91% of the households in our sample collect fuelwood, while 97% are involved in some kind of labor market activity. On average 73% of the members of each household are active in the labor market. An average household member invests roughly three hours per week in resource collection and 21 hours in the labor market. These hours, on average, are split in the following way: 8 hours in self employment and 13 hours in wage employment. The average travel time between the household location and the collection location is of 39 minutes.

Households have an average of five members, and roughly 71% of the household member are older than 15. On average, the head of the household has almost 4 years of education. 70% of the households in our sample are connected to the electric grid. The utilization rate is also high for kerosene, roughly 90% of the households, while much lower for LPG and crop residues, 14% and 23% respectively. fuelwood use is widespread - about 97% of the households in the sample uses it. 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 of Rs 1.64/kg. Villages tend to be located close to towns, with a mean distance of 14.9 km.

Even if our analysis takes place at the household level, it is interesting to have a look at 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 resource collection. A large majority of working age women, roughly 90%, are involved in resource collection. About 53% of the women in the sample also participate in the labor market. Only 5.1% of the women are involved in the labor market but not in fuel collection. The picture is

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

Table 1: Descriptive statistics

Variable	**Observations**	**Mean**	**St. Dev.**	**Min**	**Max**
<u>Household level variables</u>					
Share collecting resources	10,139	0.91	0.29	0.00	1.00
Hours per week spent in collection	10,139	2.95	3.14	0.00	36.00
Share working	10,139	0.97	0.17	0.00	1.00
Share of household in the labor market	10,139	0.73	0.28	0.00	1.00
Hours per week in the labor market	10,139	21.12	12.08	0.00	95.48
Hours per week in self-employment	10,139	8.11	10.15	0.00	85.96
Hours per week in wage activities	10,139	13.02	11.83	0.00	72.31
Travel time (min)	10,139	39.13	33.22	0.00	240
Household size	10,139	5.36	2.55	1.00	38.00
Share of Household >15 years	10,139	70.94	22.05	14.29	100.00
Years of education of the head of household	10,139	3.77	4.21	0.00	15.00
Hindu	10,139	0.89	0.31	0.00	1.00
Household income per cons unit (Rs)	10,139	13,190	21,753	2.26	830,000
Involved in Conflict	10,139	0.43	0.49	0.00	1.00
Electricity connection	10,139	0.69	0.46	0.00	1.00
fuelwood	10,139	0.96	0.20	0.00	1.00
Crop residue	10,139	0.23	0.42	0.00	1.00
Kerosene	10,139	0.90	0.30	0.00	1.00
LPG	10,139	0.14	0.35	0.00	1.00
<u>Village level variables</u>					
fuelwood price (Rs/kg)	8,700	1.60	2.12	0.01	40.00
Employment program in village	10,139	0.88	0.32	0.00	1.00
Distance to nearest town (in km)	10,139	14.91	11.08	1.00	85.00
Village population bet 1,001 and 5,000	10,139	0.58	0.49	0.00	1.00
Village population over 5,000	10,139	0.15	0.36	0.00	1.00
Average unskilled wage (Rs)	10,139	53.75	24.62	6.00	524.50
Unskilled wage for males (Rs)	10,139	61.83	36.69	6.00	999.00
Unskilled wage for females (Rs)	10,139	45.67	19.41	6.00	150.00

somewhat different for men. Less of the men (60%) collect fuelwood while 83% are involved in the labor market. About a third of the men (32.5%) participate in the labor market but do not collect fuelwood.

Table 2: fuelwood collection and labor force participation by gender

	Not participanting in the labor force	Participating in the labor force	Total
Women			
Not collecting	6.9%	5.1%	12.0%
Collecting	35.3%	52.7%	88.0%
Total	42.2%	57.8%	100%
Men			
Not collecting	7.2%	32.5%	39.7%
Collecting	9.9%	50.4%	60.3%
Total	17.1%	82.9%	100%

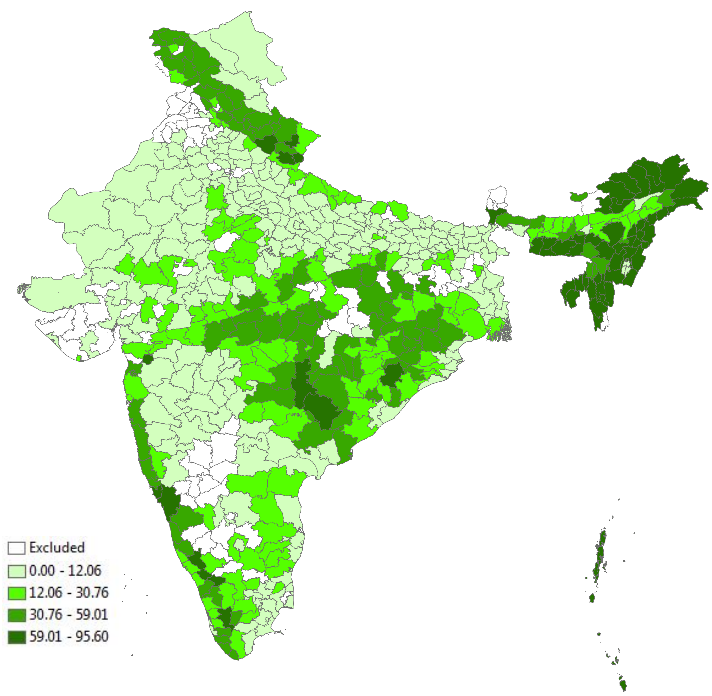
Roughly a fifth of our sample live in districts which lost forest cover between between 2000 and 2004. This information is taken from the Forest Survey of India reports (2001, 2005), which covers 368 districts.[6] In 2004, national forest cover was estimated at 20.6% (Forest Survey of India, 2005).[7] Figure 2 shows the variation in forest cover across districts.[8] For example, the state of Haryana has only a 4% cover, while Lakshadweep has 86% coverage. Most of the deforestation is occurring 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 the rate of deforestation during 2000-04 has been significant. Roughly 41% of forest area has been degraded by some degree.

[6]These reports give forest cover and deforestation data by state and by district biannually. This is based on satellite images from 2000 and 2004 analyzed using GIS technology at a scale of 1:50,000.

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

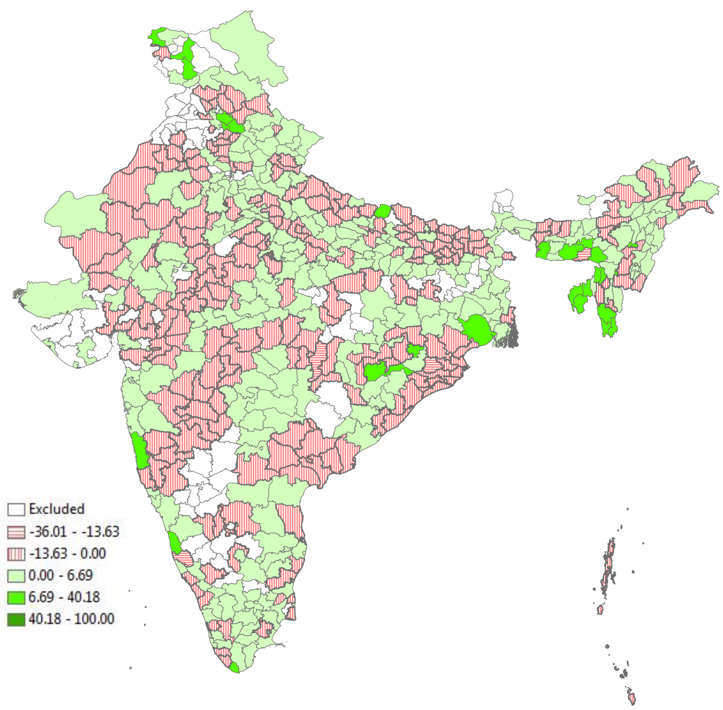
[8]Table A.1 reports forest cover for all states for 2000 and 2004.

Figure 2: Forest cover 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 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.

4 Empirical approach and results

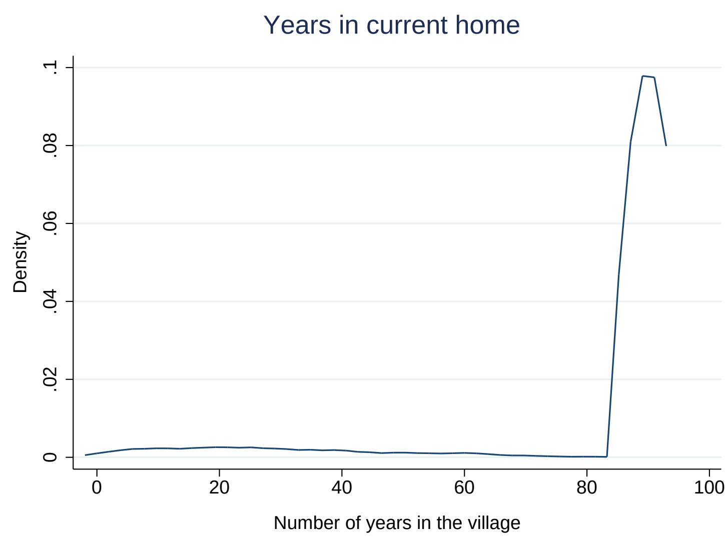
4.1 Identification

Fuel collection decisions depend on factors that may contemporaneously affect labor market decisions. 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. If this is the case, by running a simple Ordinary Least Squares (OLS) regression, because of the correlation between the variable of interest and the error term, we are not identifying a causal relationship. We deal with this endogeneity issue by using an instrumental variable approach. We instrument collection time with the distance (measured in minutes) between the household and the collection location. The mean district-level distance from the household to the collection location is negatively correlated with the degree of deforestation in the district. Therefore, this distance is a plausible proxy for forest cover, 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 33 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



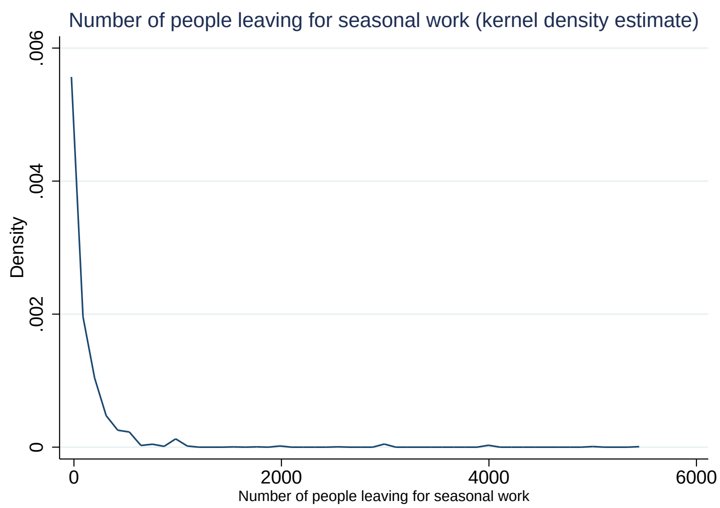
Notes: This is a kernel density estimation of the number of years households spent living in the same house. Data are censored at 90.

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

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

Figure 5



Notes: This is a kernel density estimation of the number of workers leaving the village for seasonal work.

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 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

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

where HC denotes the hours spent in fuelwood collection per individual of 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)

Table 3: First stage

	Dependent variable collection time (log)			
	(1)	(2)	(3)	(4)
Travel time (log)	0.288***	0.283***	0.277***	0.276***
	(0.010)	(0.010)	(0.010)	(0.010)
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	10,139	10,139	10,139	10,139
F-stat first stage	871.27	823.99	753.05	756.29

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.

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 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 firelwood 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 B.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

[10] 2.95x60x0.026.

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 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

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

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

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

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.

Table 4: Second stage

	Dependent variable: working time (log)			
	(1)	(2)	(3)	(4)
All activities:				
Hours spent collecting (log)	0.141***	0.154***	0.112***	0.113***
	(0.033)	(0.032)	(0.032)	(0.033)
Self-employment:				
Hours spent collecting (log)	−0.117*	−0.066	−0.057	−0.097*
	(0.060)	(0.057)	(0.060)	(0.057)
Wage activities:				
Hours spent collecting (log)	2.606***	2.440***	1.799***	1.919***
	(0.485)	(0.480)	(0.500)	(0.502)
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	10,139	10,139	10,139	10,139

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.

The positive effect of longer collection times on wage earning activities may, at first, 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 higher (19.5 Rs/10kg) in districts that did experience deforestation between 2001 and 2005 then in districts that experienced reforestation (13.4 Rs/10kg). The price difference is also significant between districts where forest cover represents less than 5% of the geographical area (26.2 Rs/10kg) and those with a higher share (15.8 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.

Table 5: Relationship between forest cover and fuel wood price

	Fuelwood price (Rs/kg)
Forest cover $< 100km^2$	1.93
Forest cover $> 100km^2$ and $< 500km^2$	1.58
Forest cover $> 500km^2$ and $< 1500km^2$	1.52
Forest cover $> 1500km^2$	1.51
Forest cover changes negatively between 2002 and 2004	1.35
Forest cover does not change between 2002 and 2004	1.65
Forest cover changes positively between 2002 and 2004	1.77
Forest cover represents less than 5% of geographical area	1.04
Forest cover represents more than 5% of geographical area	2.51

Source: Data on fuelwood price come from the IHDS dataset, while data on the district forest cover are from the Forest Survey of India 2001 and 2005.

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 in the City

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 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 < 20km	Distance to town ≥ 20km – < 30km	Distance to town ≥ 30km
fuelwood price (Rs/10kg)	17.26	15.38	14.61

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 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 7: Descriptive statistics for buyers and non buyers

Variable	**Observations**	**Mean**	**St. Dev.**	**Min**	**Max**
Buyers					
Share collecting resources	1,322	0.60	0.49	0.00	1.00
Hours per week in collection	1,322	1.42	2.36	0	15.67
Share working	1,322	0.96	0.20	0.00	1.00
Share of household in the labor market	1,322	0.65	0.29	0.00	1.00
Hours per week in the labor market	1,322	19.65	11.97	0.00	86.54
Hours per week in self-employment	1,322	6.80	9.79	0.00	69.23
Hours per week in wage activities	1,322	12.85	11.67	0.00	69.23
Travel time (min)	1,322	22.54	31.53	0.00	180
Household size	1,322	5.39	2.44	1.00	19.00
Share of Household >15 years	1,322	69.77	22.67	16.67	100.00
Years of education of the head of household	1,322	4.37	4.28	0.00	15.00
Share of Women in the household	1,322	51.43	17.49	0.00	1.00
Hindu	1,322	0.82	0.39	0.00	1.00
Household income per cons unit (Rs)	1,322	13,260	13,828	80	151,400
Involved in Conflict	1,322	0.43	0.50	0.00	1.00
Electricity connection	1,322	0.71	0.45	0.00	1.00
fuelwood	1,322	1.00	0.00	1.00	1.00
Crop residue	1,322	0.18	0.39	0.00	1.00
Kerosene	1,322	0.92	0.28	0.00	1.00
LPG	1,322	0.19	0.40	0.00	1.00
Non buyers					
Share collecting resources	5,289	1.00	0.00	1.00	1.00
Hours per week in collection	5,289	3.26	3.10	0.02	28.00
Share working	5,289	0.98	0.15	0.00	1.00
Share of household in the labor market	5,289	0.76	0.26	0.00	1.00
Hours per week in the labor market	5,289	22.71	12.24	0.00	95.48
Hours per week in self-employment	5,289	8.98	10.76	0.00	85.96
Hours per week in wage activities	5,289	13.72	12.37	0.00	72.31
Travel time (min)	5,289	44.15	30.84	1.00	180
Household size	5,289	5.36	2.58	1.00	31.00
Share of Household >15 years	5,289	71.44	21.93	18.18	100.00
Years of education of the head of household	5,289	3.58	4.14	0.00	15.00
Share of Women in the household	5,289	51.22	16.93	0.00	1.00
Hindu	5,289	0.91	0.29	0.00	1.00
Household income per cons unit (Rs)	5,289	12,831	20,461	2.26	718,750
Involved in Conflict	5,289	0.39	0.49	0.00	1.00
Electricity connection	5,289	0.72	0.45	0.00	1.00
fuelwood	5,289	0.99	0.11	0.00	1.00
Crop residue	5,289	0.21	0.41	0.00	1.00
Kerosene	5,289	0.92	0.27	0.00	1.00
LPG	5,289	0.12	0.32	0.00	1.00

Table 8: First stage buyers and non-buyers

	Dependent variable: collection time (log)			
	(1)	(2)	(3)	(4)
Buyers:				
Travel time (log)	0.260***	0.258***	0.256***	0.255***
	(0.013)	(0.013)	(0.013)	(0.012)
Distance to nearest town (log)				0.016
				(0.023)
Non-buyers:				
Travel time (log)	0.186***	0.183***	0.176***	0.178***
	(0.023)	(0.023)	(0.022)	(0.022)
Distance to nearest town (log)				−0.030*
				(0.017)
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	10,139	10,139	10,139	10,139

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. 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.

Table 9: Second stage non buyers

	Dependent variable:			
	working time (log)			
	(1)	(2)	(3)	(4)
All activities:				
Hours spent collecting (log)	0.030	0.035	0.014	0.004
	(0.080)	(0.074)	(0.078)	(0.080)
Distance to nearest town (log)				0.022
				(0.019)
Self employment:				
Hours spent collecting (log)	-0.381^{**}	-0.274	-0.277	-0.342^{*}
	(0.192)	(0.191)	(0.203)	(0.190)
Distance to nearest town (log)				0.116^{***}
				(0.044)
Wage employment:				
Hours spent collecting (log)	3.460^{**}	2.761^{**}	2.491^{*}	2.670^{*}
	(1.517)	(1.393)	(1.443)	(1.417)
Distance to nearest town (log)				-0.397
				(0.363)
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	5,289	5,289	5,289	5,289

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 specification

	Dependent variable: collection/working time (log)			
	First	Tot	Self	Wage
	(1)	(2)	(3)	(4)
Travel time (log)	0.188***			
	(0.024)			
Hours spent collecting (log)		−0.075	−0.649***	2.194
		(0.089)	(0.199)	(1.843)
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	5,289	5,289	5,289	5,289

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.

4.2.1 Identifying the real net-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

Table 11: Second stage buyers

	Dependent variable: working time (log)			
	(1)	(2)	(3)	(4)
All activities:				
Hours spent collecting (log)	0.219***	0.197***	0.166**	0.149**
	(0.071)	(0.068)	(0.068)	(0.070)
Distance to nearest town (log)				0.053
				(0.040)
Self employment:				
Hours spent collecting (log)	−0.017	0.009	0.012	−0.101
	(0.141)	(0.138)	(0.142)	(0.138)
Distance to nearest town (log)				0.075
				(0.065)
Wage employment:				
Hours spent collecting (log)	3.087***	2.659**	2.251**	2.580**
	(1.169)	(1.077)	(1.061)	(1.048)
Distance to nearest town (log)				0.375
				(0.641)
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	1,322	1,322	1,322	1,322

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 specification

	Dependent variable: collection/working time (log)			
	First	Tot	Self	Wage
	(1)	(2)	(3)	(4)
Travel time (log)	0.251***			
	(0.017)			
Hours spent collecting (log)		0.170**	−0.041	2.036
		(0.079)	(0.179)	(1.255)
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	1,322	1,322	1,322	1,322

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.

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

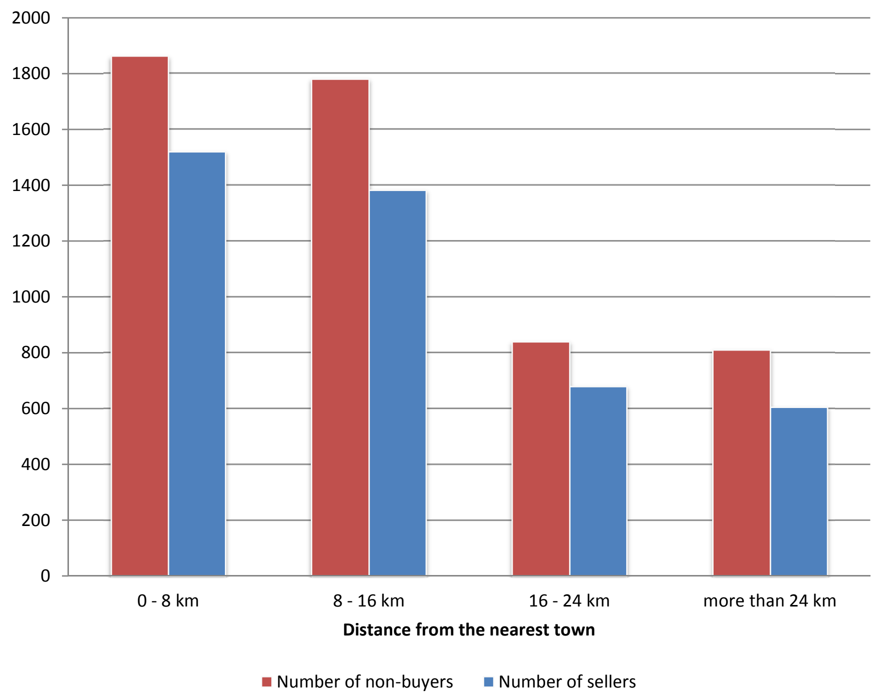
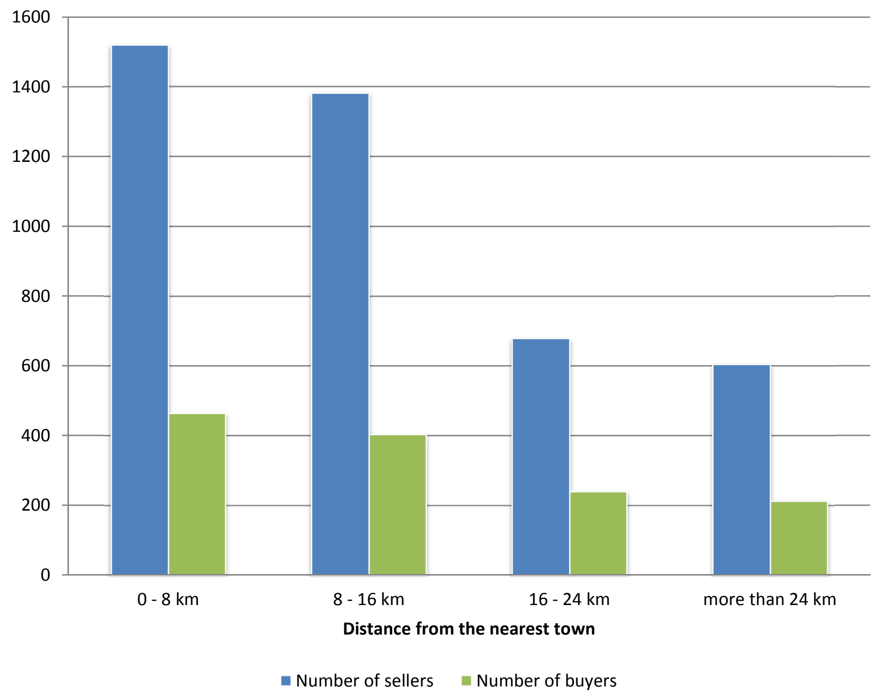


Figure 7 shows the evolution of the number of sellers and buyers as we move to villages located farther from a town. The number of sellers decreases by more than a half as we move away from an urban area, this result is aligned with our theoretical model: sellers tend to be located close to urban centers, where they can obtain the highest price and

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



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: Sellers

	Dependent variable: collection/working time (log)			
	First	Tot	Self	Wage
	(1)	(2)	(3)	(4)
Travel time (log)	0.177***			
	(0.028)			
Hours spent collecting (log)		0.091	−0.410*	4.407**
		(0.108)	(0.240)	(1.884)
Distance to nearest town (log)	−0.052***	0.035	0.111*	−0.173
	(0.019)	(0.023)	(0.058)	(0.483)
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	3,554	3,554	3,554	3,554

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 13 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 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 14 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 14: Sellers – village fixed effects specification

	Dependent variable: collection/working time (log)			
	First	Tot	Self	Wage
	(1)	(2)	(3)	(4)
Travel time (log)	0.179***			
	(0.027)			
Hours spent collecting (log)		−0.007	−0.676***	3.994*
		(0.113)	(0.256)	(2.168)
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	3,554	3,554	3,554	3,554

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 Concluding Remarks

This paper studies the effect of reduced forest cover on time allocation by households. We find that increased time taken by households to travel to the collection site induces households to increase the time spent in collection. Costlier access to resources leads households to spend more time in wage earning occupations, but does not affect time spent in self-employment activities. By differentiating the population into buyers and sellers of fuelwood, we can see a difference in the response of the two groups to costlier access to forests. Sellers reduce their time in self-employment and spend more time collecting. Buyers spend more time in wage activities. This makes economic sense because buyers of fuelwood must earn more income to pay for costlier energy, while sellers profit from scarcity and reduce their time in other activities.

Distance to the nearest town has a differential impact on these two groups. When households are located far from towns, there is less incentive for sellers to collect fuelwood since prices are likely to be low in distant locations. Buyer behavior is not sensitive to distance from towns.

The main contribution of our paper is in recognizing the role of reduced forest access in rural labor market outcomes and showing that households may have different objectives when they engage in resource collection. Those who collect to buy may respond differently to scarcity and to market forces than those who collect to sell. For forest policy to be effective, it must be sensitive to these multiple goals. 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 energy-efficient appliances such as stoves.

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.

Burgess, R., Hansen, M., Olken, B., Potapov, P., and Sieber, S. (2012). The Political Economy of Deforestation in the Tropics. *The Quarterly Journal of Economics*, 127(4):1707–1754.

Cavendish, W. (2000). Empirical Regularities in the Poverty-Environmental Relationship of Rural Households: Evidence from Zimbabwe. *World Development*, 28(11):1979–2003.

Chakravorty, U. and Gunatileke, H. (2003). Protecting Forests Through Farming. A Dynamic Model of Nontimber Forest Extraction. *Environmental & Resource Economics*, 24(1):1–26.

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.

Cropper, M. and Griffiths, C. (1994). The Interaction of Population Growth and Environmental Quality. *American Economic Review*, 84(2):250–54.

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.

Kamanga, P., Vedeld, P., and Sjaastad, E. (2009). Forest Incomes and Rural Livelihoods in Chiradzulu District, Malawi. *Ecological Economics*, 68(3):613–624.

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.

Nankhuni, F. and Findeis, J. (2003). Natural Resource Collection Work and Schooling in Malawi. 2003 Annual Meeting, August 16-22, 2003, Durban, South Africa 25829, International Association of Agricultural Economists.

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.

Wagura Ndiritu, S. and Nyangena, W. (2010). Environmental Goods Collection and Childrens Schooling: Evidence from Kenya. Discussion Papers dp-10-18-efd, Resources For the Future.

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 B.2: First stage

	Dependent variable collection time			
	(1)	(2)	(3)	(4)
Travel time (log)	0.288***	0.283***	0.277***	0.276***
	(0.010)	(0.010)	(0.010)	(0.010)
Household size		0.007***	0.009***	0.008***
		(0.002)	(0.002)	(0.002)
Share of household >15 years		−0.000	−0.000	−0.000
		(0.000)	(0.000)	(0.000)
Years of schooling of the head of household		−0.003	−0.002	−0.003
		(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		−0.019	−0.022	−0.022
		(0.019)	(0.019)	(0.019)
Household income (log)		−0.023***	−0.014***	−0.014**
		(0.006)	(0.005)	(0.005)
Involved in conflict		0.014	0.014	0.014
		(0.023)	(0.023)	(0.023)
Electricity use			−0.036**	−0.035**
			(0.014)	(0.014)
fuelwood use			0.037	0.040
			(0.032)	(0.033)
Crop residues use			0.075***	0.076***
			(0.028)	(0.028)
Kerosene use			−0.000	0.001
			(0.025)	(0.025)
LPG use			−0.095***	−0.094***
			(0.020)	(0.020)
Employment program in village				0.006
				(0.031)
Distance to nearest town (log)				−0.010
				(0.012)
Village population btw 1001 and 5000				−0.018
				(0.023)
Village population above 5000				−0.029
				(0.033)
Unskilled average wage (log)				−0.061
				(0.039)
Observations	10,139	10,139	10,139	10,139
F-stat first stage	871.27	823.99	753.05	756.29

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