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The Effect of Forest Access on the Market for Fuelwood in India

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Summary

Fuelwood collection is often cited as the most important cause of deforestation in developing countries. Use of fuelwood in cooking is a leading cause of indoor air pollution. Using household data from India, we show that households located farther away from the forest spend more time collecting. Distant households are likely to sell more fuelwood and buy less. That is, lower access to forests increases fuelwood collection and sale. This counter-intuitive behavior is triggered by two factors: lower access to forests (a) increases the fixed costs of collecting, which in turn leads to more collection; and (b) drives up local fuelwood prices, which makes collection and sale more profitable. We quantify both these effects. Using our estimates we show that a fifth of the fuelwood collected is consumed outside of rural areas, in nearby towns and cities. Our results imply that at the margin, fuelwood scarcity may lead to increased collection and sale, and exacerbate forest degradation.

Keywords: Energy Access, Cooking Fuels, Deforestation, Forest Cover, Fuelwood Collection

JEL Classification: D10, O13, Q42

We would like to thank seminar participants at Michigan, Maryland, RFF, Tufts, Georgia Tech, Paris, Rennes, World Bank, the Chinese Academy of Sciences, the Montreal Workshop in Environmental and Resource Economics, Ryerson, Ottawa, Toulouse, Orleans, the AERE Summer Conference, the 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. We are grateful to Kyle Emerick, Sumeet Gulati, Sebastien Houde, Kelsey Jack, Ryan Kellogg, Shaun McRae, Gib Metcalf, Gautam Rao, E. Somanathan and Rob Williams for valuable comments that greatly improved the paper. We acknowledge generous funding from the French Agence Nationale de la Recherche (ANR) grant number ANR-14-CE05-0008.

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May 28, 2018

Abstract

Fuelwood collection is often cited as the most important cause of deforestation in developing countries. Use of fuelwood in cooking is a leading cause of indoor air pollution. Using household data from India, we show that households located farther away from the forest spend more time collecting. Distant households are likely to sell more fuelwood and buy less. That is, lower access to forests *increases* fuelwood collection and sale. This counter-intuitive behavior is triggered by two factors: lower access to forests (a) increases the fixed costs of collecting, which in turn leads to more collection; and (b) drives up local fuelwood prices, which makes collection and sale more profitable. We quantify both these effects. Using our estimates we show that a fifth of the fuelwood collected is consumed outside of rural areas, in nearby towns and cities. Our results imply that at the margin, fuelwood scarcity may lead to increased collection and sale, and exacerbate forest degradation.

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1 Introduction

An emerging literature in economics focuses on energy decisions of the poor, especially in developing nations (see Gertler et al., 2016). More than a billion of them do not have access to commercial energy such as electricity and natural gas. About two billion people worldwide depend on fuelwood to meet their cooking and heating needs. The demand for fuelwood for cooking and heating is often cited as the most important cause of deforestation, ahead of other demands for forest products such as furniture and paper.[1] Fuelwood collection not only has an adverse effect on forests, it is a major contributor to indoor air pollution, both in villages and towns.[2] In 2017, the Government of India declared an end to federal subsidies for LPG (Liquefied Petroleum Gas), a substitute for fuelwood in cooking, raising concerns that this would increase fuelwood use and have an adverse impact on indoor air quality.[3]

This large demand for fuelwood suggests that many poor people collect and sell it, mainly in local markets, because of its low value-to-volume ratio.[4] However, there are very few studies on the market for fuelwood in developing countries. Many papers have focused on the existence of an Environmental Kuznets Curve.[5] Others have examined how local incentives affect deforestation and fuelwood collection (see Burgess et al., 2012; Edmonds, 2002).

This paper focuses on household decisions to collect, buy and sell fuelwood in rural India, using cross-sectional survey data.[6] Using the variation in the time it takes for households to walk to the forest to collect wood, we estimate the causal effect of this travel time on fuelwood collection, sale and purchase by households. We show that longer travel times lead

[1]About 58% of the energy supply in Africa comes from fuelwood and charcoal (Specht et al., 2015). In India, according to the Ministry of Statistics, more than two-thirds of the rural and about 14% of the urban population relies on fuelwood for cooking (see e.g., https://scroll.in/article/747551/67-of-indias-rural-households-still-use-firewood).

[2]The World Health Organization suggests that indoor air pollution from household cooking is the leading cause of environmental deaths, killing about 4.3 million people annually, according to Hanna et al. (2016).

[3]"Govt orders LPG prices to be hiked by Rs 4 per month", *The Times of India*, July 31st 2017; Singh, S., "How withdrawal of LPG subsidy can raise India's healthcare costs," *Business Standard*, August 3rd 2017.

[4]The World Bank estimates that 275 million people in India depend on forestry for at least part of their livelihood (Milne et al., 2006).

[5]See Baland et al. (2010) on the effect of rising living standards on fuelwood collection by households in rural Nepal and Foster and Rosenzweig (2003) on the link between afforestation in India and the increased demand for forest products at the local level.

[6]Micro-level surveys show that a significant share of rural Indian households (25%) buy fuelwood and more than 90% of all households collect it on a regular basis. This thriving market for fuelwood has been noted by other scholars, e.g., Hanna et al. (2016) find that 83% percent of their survey households collected wood, 35% of them bought and 20% were sellers at some point in time. Those who reported collecting wood in their survey spent more than five hours on average during a single trip.

to increased collection of fuelwood and sales, while reducing the volumes bought. At the extensive margin, higher travel times increase the probability that a household is a net seller of fuelwood, and decrease the likelihood of the household buying fuelwood in the market. These two effects together suggest that in regions with lower forest cover and longer travel times, more fuelwood is collected and sold.

Our analysis suggests that areas that have undergone deforestation in the past may see a downward spiral over time: a reduction in forest cover that triggers increased extraction and rising wood prices, which leads to even more deforestation.

We first develop a model in which a household allocates time to work for wages and collects fuelwood that it can consume in-house for cooking and heating. The household can buy or sell fuelwood in the market. Higher travel times increase the fixed costs of collecting fuelwood. They also increase local fuelwood prices. Both these effects lead to increased collection and sales, and a reduction in fuelwood purchased by households. These predictions are tested using survey data from Indian households. We use the India Human Development Survey (Desai and Vanneman, 2005) which identifies household who collect or buy fuelwood. We combine this cross-sectional data with another household survey from the National Sample Survey (2005) to elicit which households in our IHDS sample are net sellers of fuelwood. We regress household level outcomes for fuelwood collection, sales, purchase and consumption on the distance of the household from the forest, controlling for household characteristics such as income, education, household size and farm size. We show that our results are robust with district fixed effects, where we control for village-level fuelwood prices, and with village fixed effects, when the variation in travel times comes only from within-village variation of the distance of each household to the forest.

We perform several robustness checks. Because fuelwood sales in our sample are estimated, we check if the results hold with alternative definitions of what constitutes a seller household. Since many households are either sellers or buyers or do not engage in buying or selling, many observations of the outcome variables have zero values, so we re-estimate using a Tobit model. To ensure that our results are not due to seller households simply collecting wood from locations other than where the rest of the village collects, we estimate using only the sub-sample of sellers and show that the same effects obtain – larger travel times lead to higher volumes collected and sold. We also account for differences in the ownership of forests from which collection is done and check that the results hold when fuelwood is collected from privately-owned as well as public forests.

Aggregating the volumes collected and consumed for the whole country, we estimate that about 18% of the total fuelwood collected is not accounted for by village consumption – it is consumed in nearby towns and cities.[7] If we distribute this missing fuelwood among the largest 46 Indian towns and cities (with population in excess of a million) in proportion to their populations, we can provide a rough estimate of the pollution load in cities that originates from burning fuelwood that is collected in nearby rural areas. By our calculations, just one city, New Delhi, receives a $PM_{2.5}$ load of 24-35 tons per day (a concentration of 18-25 $\mu g/m^3$) from burning this leaked fuelwood, roughly 15-20% of its total load.[8] We find that a 10% decrease in forest cover will lead to an increase in fuelwood collection by 0.52% and a rise in the total volume of leaked fuelwood by 2.74%.

These findings have important policy implications. Our estimates suggest that the size of the fuelwood market is large. Moreover, households respond to economic incentives. They collect more when the fixed cost of collection is higher, and when the price of fuelwood is high. Government policies that lead to the removal of subsidies for cleaner fuels, such as LPG and natural gas, may lead to increased fuelwood collection. Our results show that fuelwood consumption in the village is unlikely to change appreciably, which implies that increased volumes collected will be used in nearby towns and cities, with adverse impacts on urban air quality, which is already below recommended levels.

Section 2 outlines a simple model of fuelwood collection by households. Section 3 discusses the data used and the empirical strategy. Section 4 shows the main results and robustness checks. Section 5 uses our estimates to determine the size of the fuelwood market and pollution load in cities. Section 6 concludes the paper.

2 A simple model of fuelwood collection by households

In this section, we model the choice of a representative household that allocates time for collecting fuelwood either for domestic consumption or for sale. Since members of the household may make these decisions jointly, we consider all decisions at the aggregate level of the household. We abstract from considering heterogeneity across households in terms of time endowments and skill levels - issues we consider in the empirical section. Members of the

[7]The aggregate volume of fuelwood collected is equal, in terms of energy content, to about 1.5 million barrels of crude oil per day (mbpd) – roughly a third of India's annual total consumption of crude oil.

[8]Particulate loads can vary sharply between seasons, and is several times higher in winter. A study based on monitoring station data estimates that the daily $PM_{2.5}$ load in Delhi is 175 tons, and about 26% of that comes from burning of biomass (Sharma and Dikshit 2016), slightly higher than our estimates. Each 10 $\mu g/m^3$ increase in fine particulate air pollution is estimated to cause a 4%, 6%, and 8% increase in the risk of all-cause, cardiopulmonary and lung cancer mortality, respectively (Pope III et al., 2002).

household can travel to the nearest forest and collect fuelwood. The fuelwood can be used to meet energy needs within the household or sold in the local village market at a price p. This price is determined by equating the aggregate supply and demand for fuelwood in the village. Individual households are assumed to be small and not able to affect this fuelwood price. Suppose that the household collects fuelwood from the forest located at distance x. We assume that everyone walks to the forest, which is the norm in rural India. Rural infrastructure such as roads mostly connects villages to nearby towns. It would be highly unusual if there was a paved road to the nearby forest.[9]

The household may consume fuelwood and an alternative energy source for cooking, such as kerosene (or Liquefied Petroleum Gas (LPG), animal dung or agricultural residue) which we capture by the subscript k. Each household is assumed to be of the same size and therefore uses the same amount of cooking energy every week, denoted by $\bar{q_u}$. Let the time spent in collecting (as distinct from traveling to the forest) by the household be defined by t_c. Let us assume that the volume of fuelwood collected per unit time (the collection rate) is constant for all households in the village and given by v so that the total fuelwood collected each week is $q_c = vt_c$. Let the volume of fuelwood sold per week by our household be denoted by q_s and the volume bought by q_b. The amount of the alternative fuel used by the household is denoted by q_k. Kerosene produces more energy per unit volume than fuelwood, which is denoted by an efficiency parameter θ, where $\theta > 1$.[10] We can thus write the condition for household fuelwood energy use as

$$\bar{q_u} = q_c + q_b - q_s + \theta q_k. \tag{1}$$

That is, household energy consumption equals fuelwood collected plus fuelwood bought net of sales, plus the quantity of kerosene consumed.

Our household is endowed with total time $\bar{t_h}$. One could think of this variable as the sum of the time endowment for members of the household. This time can be split into the time spent traveling to the forest and collecting fuelwood, given by $x + t_c$ and working for wages in an alternate sector, given by t_w.[11] Thus the time constraint can be written as

[9] It is possible that some households use other modes of transportation such as bicycles or less frequently, motorized scooters to transport fuelwood. In the data, about 57% of our households have a bicycle, 10% own scooters and 0.7% own cars. We deal with this issue in the empirical section. Here we normalize by assuming that everyone walks at the same speed, and thus x can be measured in time units.

[10] θ may be smaller than unity if the alternative fuel is dung or crop residue.

[11] The survey we use does not have trip information. So we are unable to model the number of trips per week. However, to the extent that the volume of fuelwood collected is constrained by a person's carrying capacity, the total time spent per week is a linear relation of the number of trips, so in essence, we assume

$$\bar{t_h} \geq x + t_c + t_w. \tag{2}$$

We can now write the household's maximization problem as

$$\max_{q_s, q_b, q_k, t_c, t_w} p(q_s - q_b) + t_w \bar{w} - p_k q_k, \tag{3}$$

subject to conditions (1) and (2). The choice variables are the quantities of fuelwood bought and sold, the amount of the alternate fuel kerosene used, and the time spent in collecting fuelwood and working for wages. The Lagrangian can be written as

$$Ł = p(q_s - q_b) + t_w \bar{w} - p_k q_k + \lambda[\bar{t_h} - t_c - x - t_w] - \beta[\bar{q_u} - q_c - q_b + q_s - \theta q_k]. \tag{4}$$

We can derive and interpret the first order conditions for this problem. Both buyers and sellers must satisfy the condition $p = \beta$, i.e., the price of fuelwood must equal the shadow price of fuelwood in the household which is given by β. If the household uses positive amounts of the alternate fuel kerosene, then it must satisfy the condition $p_k = \theta\beta$. That is, the price of kerosene is equated to the shadow price of fuel in the household, adjusted by the fuel efficiency of kerosene, given by θ.[12] The household spends time collecting fuel to satisfy the relationship $\lambda = v\beta$, where λ is the opportunity cost of time. It equals the fuelwood collected per unit time v times the reservation price of fuelwood, β.[13] Finally, households earn a wage $\bar{w}$ which in equilibrium is equated to the opportunity cost of time, λ.

The above framework suggests that households compare the wages received $\bar{w}$ by working in other sectors (e.g., in construction or as agricultural labor) with the returns from selling fuelwood. It is likely that if the household has skilled labor then its wage rate may be high, in which case, it earns wages and satisfies domestic fuel needs by simply buying fuelwood in the market. Conversely, those with lower wages may find selling fuelwood a more lucrative proposition. Of course that decision also depends on the current price of fuelwood in the village. A higher price, *ceteris paribus*, is likely to induce increased supply, either through a greater number of households collecting and selling, or each of them trading larger volumes.

For the household, the average cost of collecting fuelwood is equal to the price, assuming a zero-profit condition. This is given by $\frac{(t_c+x)\lambda}{vt_c} = p$. On the left hand side, we have the

that everyone makes one trip a week.

[12] For example, if kerosene is twice as efficient as fuelwood, the price of kerosene will be twice that of the reservation price of fuel, β.

[13] The units on the right hand side are volume of fuelwood (say in kilograms) collected per hour times the price in \$ per kilogram, which matches the left hand side units, \$/hour.

total value of time spent collecting fuelwood, which equals $t_c + x$ times the household's shadow price of time λ. This is divided by the volume of fuelwood collected, given by vt_c. That is, the price of fuelwood must equal the average revenue from collecting it. Implicitly we assume that because fuelwood is a common property resource, rents from collecting are driven to zero. This yields $t_c = \frac{\lambda x}{vp-\lambda}$. Both sides of this equation are positive. If the distance to the forest x is higher, assuming that for small changes in x the shadow price of time λ and fuelwood price p do not change, we get the relationship $\frac{dt_c}{dx} > 0$. Intuitively, when the household is located farther from the forest, households spend more time collecting fuelwood. This is because getting to the forest is more costly in terms of time, hence to break even, more time must be spent collecting and a larger volume collected. In our simple formulation, this also means more fuel is collected.[14]

From the right hand side of (1), more collection, *ceteris paribus*, implies more fuelwood sold and less fuelwood bought in the market. It is reasonable to assume that households either sell or buy fuelwood or do neither of these, but do not simultaneously engage in both activities. In that case, for sellers, the quantity bought $q_b = 0$; hence the net fuel consumed at home, given by $q_c - q_s$, is unlikely to change since both increase when distance to forest increases. For buyers, $q_s = 0$; hence the net fuel consumed at home is given by $q_c + q_b$ which also remains unchanged with an increase in travel time and distance to forest, since the quantity collected increases while the quantity bought declines.

Figure 1 shows the effect of travel time in determining fuelwood price and quantity. When villages are located close to abundant forests, so that travel times are low, the fuelwood supply curve is given by S_1 and short run demand by D_1 so that the quantity of fuelwood supplied is Q_1 at price P_1. In villages with low forest cover, travel times are high, so the supply curve is higher at S_2. The price of fuelwood is higher at P_2. Buyers in forest-scarce regions collect more and switch to alternate fuels while suppliers sell more fuelwood. Hence long run demand in forest-scarce regions may decline to D_2 and supply may rise to S_3. The equilibrium price falls to P_3. Quantity may rise or fall.

As observed from the figure, there are two distinct effects of travel time on the household's decision to buy or sell fuelwood. With a rise in travel time within villages, fewer households may collect since some may find alternative occupations more rewarding. However, those who collect now face a higher fixed cost of accessing forests, hence they collect more. Sellers sell more. In villages where prices are higher, sellers sell more and buyers buy less. We can

[14]In a more complicated model, we could specify differential forest densities – for instance, in forests closer to the village, forest density may be lower simply because more fuelwood has already been collected. However, here we abstract from this issue.

summarize these results as follows:

Proposition: *Households living farther from the forest spend more time collecting fuelwood. They also collect more. Sellers living farther away sell more wood, and buyers buy less. The quantity consumed by households remains unchanged with distance to forest.*

3 Data and empirical specification

In this section, we discuss the data used and the procedure adopted to estimate household fuelwood consumption and sales. We use the rural section of the 2005 round of the India Human Development Survey (IHDS) which is a nationally-representative survey of households covering 26,734 rural households in 1,503 villages.[15] It contains information on a broad set of economic characteristics at the level of the individual, household and village. Specifically, household members are asked about the time spent collecting fuelwood each week, monthly expenditures and quantity purchased. Respondents are asked the one-way distance (in minutes) to their fuelwood source.[16] We will refer to this variable as travel time. We take the household as the unit of analysis because fuel collection decisions are likely made jointly by members of the household. Household travel time is the main determinant variable of interest in our empirical analysis: as we see later, these travel times exhibit significant variation within and across villages, which we exploit.

Summary statistics of IHDS sample

Table 1 reports means and standard deviations for the variables used from the IHDS survey. The main variables are averages within each household among all adult members (men and women between 15-65 years of age). For example, for the variable collection time, we aggregate the time spent collecting by each adult and divide by the number of adults in the household.[17] We classify summary statistics by roughly equal intervals of travel time (in minutes) to the fuelwood collection site. Households in our sample are about uniformly split between the three intervals: 1,859 households travel less than 25 minutes to reach the fuelwood collection site; 1,884 travel between 25 and 50 minutes, and 1,823 households travel

[15]We use the 2001 Census definition for rural and urban households.

[16]The IHDS survey asks respondents,"How many minutes does it typically take one way to the area where you collect fuel?"

[17]We do not consider individuals older than 65 because they mostly do not participate in fuelwood collection. Children below 15 too do not actively participate in collection – on average girls spend 16 minutes per week and boys 10 minutes in fuelwood collection. Roughly 10% of households reported that their children collect.

more than 50 minutes. For the whole sample, mean one-way travel time is 38.7 minutes, with a standard deviation of 32.24 minutes. The table reports data for the time spent collecting fuelwood and the volume of fuelwood bought by households. On average, households spend nearly 3 hours per week collecting fuelwood. Those that travel farther spend more time collecting, as indicated in the first three columns. The time spent collecting does not include the time spent traveling to the fuelwood site.[18] Approximately 16% of the households in the sample buy fuelwood. Across the entire sample, households buy an average of 39.5 kilograms per month. Households that travel farther buy less.

The table shows that annual income per adult equivalent is higher for those in the lowest tertile for travel time.[19] The share of households below the poverty line is higher for households in the highest tertile of travel time. The heads of these households are also less likely to be educated.

Years in current home corresponds to how long the family has lived in their current dwelling. On average, the family has lived in the same location for about 83 years, with little difference among households with different travel times; the histogram for this variable is depicted in Figure 2. The variable other state/country corresponds to whether the family originated from a different state or country than they currently reside in – only 1% of our sample moved from elsewhere. These statistics suggest that households in our sample are not mobile.

We include indicator variables for bicycle and motorcycle/scooter ownership in case they are used for transport to and from the forest, which may induce error in reporting travel time. Walking is the most common mode of transport given undulating terrain and a lack of roads but where the land is flat, bicycles or scooters may be used to transport fuelwood.

[18] A potential measurement issue arises if respondents include travel time to the forest while reporting collection time in the survey. We believe this may not be the case for two reasons. First, about 11% of the sample report spending no time collecting, which suggests they interpret the question correctly and do not confuse collection time with travel time. Second, if collection time reports do include time traveling to the forest, the implied amount of time spent in the forest collecting fuelwood is likely to be implausible for many households. In particular, if households did include travel time, then at a minimum they undertake one fuelwood collection trip per week. Given travel time is the one-way distance, the total travel time to the forest and back is double this amount. Subtracting double the travel time from weekly collection times for households that do collect fuelwood yields negative values for more than 20% of the sample. These factors suggest that households correctly report collection time net of travel to the forest.

[19] Income includes net agricultural income, wage and salary income (agricultural and non-agricultural wages, as well as daily wages and monthly or annual salaries), non-farm business income, remittances, public benefits, property and other income. We compute income per adult equivalent using the OECD scale, i.e. one adult equivalent for the head of household, plus 0.5 adult equivalent for members older than 14 years and 0.3 for children younger than 14. Here, we do consider all individuals in the household including children and seniors.

Ownership of draft animals (bullocks, donkeys and buffaloes) may also affect the volume of fuelwood collected. Slightly more than half of the households in our sample own a draft animal.

Most households in our sample belong to the Hindu faith. IHDS respondents are asked what caste they belong to; in our sample, most households fall under either the "other backward caste" or the combined "scheduled tribe or scheduled caste" category. These lower ranked castes have travel times that are above the mean travel time, especially for scheduled castes. "Conflict in village" is a binary variable that indicates if there was significant conflict in the village. Conflict conditions may affect fuel collection and travel times – households may avoid certain forest locations or routes and not travel to distant forests. They may purchase substitutes from the market.

In Table 2 we report summary statistics of village-level variables used in the empirical analysis. We report these separately from Table 1 because the village-level variables are not reported for all households in our sample. In particular, village-level prices for fuelwood and its closest substitute kerosene are available for only 4,940 of the households in our sample.[20] The mean price for fuelwood is Rs 1.6 per kg, and for kerosene Rs 15.25 per liter. There is no clear trend in these prices across travel times.[21]

Table 2 shows the share of households living in small (population less than 1000), medium (population in the range 1001-5000) and large (population more than 5000) villages in our sample. Vertically, the three shares sum to one. One quarter of our sample households live in villages with a small population. Most households (60%) live in medium-sized villages and the remaining 15% live in villages with more than 5000 people. In small villages, a larger share of households have longer travel times; in villages with large populations, the opposite is true. This is likely due to differences in purchasing: in small, medium, and large villages, the fraction of residents buying fuelwood is 9%, 15%, and 29%.[22]

There is substantial variation within villages: Figure 3 plots the histogram for the standard deviation of travel time across villages. The standard deviation is distributed across positive values, indicating that there is significant variation in travel time within villages. In

[20]Among the three categories of travel times, we observe fuelwood and kerosene prices for 1,719, 1,689, and 1,532 households, respectively.

[21]Households report LPG prices but only for 4241 of our sample of 5566 households. We do not control for LPG prices in our baseline specification because it reduces our sample size. However, their inclusion does not affect our estimates. Our preferred specification employs village-level fixed effects, which controls for village-level factors like LPG prices.

[22]By small and large villages, we mean population since we do not know the geographical area of the village.

our sample of 733 villages, 93% have a positive standard deviation for travel time.

Estimating household fuelwood consumption and sales

In the IHDS survey, there is no direct measure of fuelwood consumption or sales by households. We estimate fuelwood consumption and sale by using another survey – the 61st round of the National Sample Survey (NSS) published in 2005. Like the IHDS, the NSS is a nationally-representative survey and asks households how much fuelwood they consume in a month, but does not contain information on household fuelwood collection or variables such as the distance to fuelwood source, which are in the IHDS. Though households are not the same in the two surveys, we develop an approach to predict fuelwood consumption and sales for a household reported in the IHDS data, based on estimation using NSS data.[23]

First, we use the NSS data to estimate, for each district, fuelwood consumption for NSS households as a function of variables common to both surveys. We estimate separately by district so that the constant and the estimated coefficients will capture differences in climate, topography and other district characteristics that may influence fuelwood consumption. Then we use these estimated district-level coefficients and IHDS household data to predict fuelwood consumption for each of our IHDS households. We know the identity of the buyer households in the IHDS sample as well as how much they buy. For these buyer households, the fuelwood purchased is deducted from the estimated consumption to yield total amount collected per week.[24] We divide the volume collected per week by the time spent in collection by the household to obtain the household hourly collection rate. The mean collection rate for all the buyers in the village gives the average collection rate for the whole village, which is applied to the remaining (non-buying) households from that village. Collection rates are expected to be similar within a village.[25] Finally, we compare predicted fuelwood consumption to the total amount of fuelwood collected to determine whether the household has an excess amount of wood. If so, we classify this household as a net seller of fuelwood.[26]

We estimate household fuelwood consumption for each district, using NSS data as follows:

$$FC_i^{NSS} = \alpha^D + X_i^{NSS}\beta^D + \varepsilon_i, \tag{5}$$

[23]Later we address potential issues with using estimated data as an outcome variable.

[24]We make the reasonable assumption that buyers and sellers are distinct groups.

[25]Given that these forests are mostly open access resources, significant differences in collection rates between sites are likely to be equalized in equilibrium. If we do not observe any buyer in the village, we apply the mean district-level collection rate to that village (obtained in the same fashion as for the village), and if there are no buyers in a district we apply the mean state collection rate.

[26]We perform several robustness checks with alternative thresholds for excess fuelwood, detailed later.

where FC_i^{NSS} denotes fuelwood consumption in kg per month, observed for a household i in the NSS data. The vector X_i^{NSS} contains the set of household characteristics observed in both the NSS and IHDS samples, listed in Table 3, and ε_i is the error term. The table provides summary statistics for the variables common to both surveys to show that they are drawn from similar distributions. It includes household size, a dummy for whether the household is self-employed, farm size, whether the dwelling unit is owned, whether the household has a ration card and the share of household members above 15 years of age. Many studies have found household income to be a significant determinant of fuelwood consumption (e.g. Baland et al., 2010) since richer households generally use less fuelwood and more of the substitutes such as kerosene or LPG. Unfortunately, income information is not available in the NSS data set. We use several proxies: a dummy for whether the head of the household is literate and one for whether (s)he has a university degree, total household expenditures and square of expenditures in meat, fish and egg products, cereals, salt and spices. Consumption of fish, meat and cereals are strongly correlated with income (Deaton and Drèze, 2009).[27] We include the quantity of spices consumed, since they are relatively expensive and income-elastic. For several variables – age of household head, and expenditures in electricity, dung, kerosene, LPG, meat, cereals and salt, we include their squared terms, since the effect on fuelwood consumption is likely to be non-linear. There are small differences between the surveys in the average consumption of electricity, dung and cereal, as seen in Table 3.

We estimate equation (5) for each of the 237 districts in the IHDS data, the most granular geographic region for which we observe a household in both surveys. We obtain a district-specific constant $\widehat{\alpha}^D$ and district-specific coefficients $\widehat{\beta}^D$. For over 75% of the districts in the NSS sample, our regressions yield an R^2 greater than 50%. On average, equation (5) explains 63% of the variation in fuelwood consumption. Table 4 reports summary statistics for observed and predicted fuelwood consumption based on the estimation. The mean observed fuelwood consumption is 122.56 kg per month, while predicted consumption is 123.03 kg per month. Figure 4 plots the two distributions, which are quite similar.

These district-specific estimates from (5) together with IHDS household characteristics are then used to predict IHDS household fuelwood consumption, according to the equation:

$$\widehat{FC}_{id}^{IHDS} = \widehat{\alpha}^D + X_{id}^{IHDS}\widehat{\beta}^D \tag{6}$$

where $\widehat{FC}_{id}^{IHDS}$ is predicted fuelwood consumption for household i in district d observed in the IHDS data. The vector X_{id}^{IHDS} is the set of household characteristics common to both

[27] At low income levels households tend to consume more cereals and less protein such as fish and meat.

data sets. We limit the sample to only those households for which there are no missing observations, which reduces it to 5,566 households in 733 villages. Table 4 reports summary statistics for predicted consumption among IHDS households. Mean predicted consumption is larger than consumption based on NSS data and, given that IHDS consumption is estimated, the standard deviation is bigger as well. Figure 5a shows the histogram of predicted fuelwood consumption for IHDS households, conditional on households using fuelwood. Over 50% of our households consume less than 6 kg per day.

Table 5 consolidates the survey data on fuelwood collection and purchase with the estimated consumption and sales, by travel time to the forest. Households that travel farther sell more. On average, households sell about 167 kilograms per month. Fuelwood consumption does vary with proximity to the fuelwood source, but not monotonically. Households that live nearest and farthest from the fuelwood source consume the most. On average, households consume about 181 kilograms of fuelwood per month. This figure matches reasonably well with findings from other studies.[28] The largest consumers are those that spend the least time collecting, and live closest to the forest. These households have higher incomes as observed earlier. They are also the most educated.

We could compute the village fuelwood collection rate for 1,147 households. For villages where no fuelwood buyer was surveyed (2,041 households), we apply the mean district collection rate, and for the 2,370 households for which there were no village and district level buyers, we apply the state average. We obtain the collection rate for 5,558 households out of our total sample of 5,566 households.[29]

We define a seller household as one that collects more fuelwood than it consumes. This procedure yields 2,700 seller households out of the full sample of 5566 households, roughly 48%.[30] Conditional on being a seller, the mean quantity sold is 346 kg/month. Some 1,781 households (32% of our sample) do not buy or sell. Households that live farther from the forest collect more fuelwood and sell more.[31] Figure 5b shows the histogram of predicted fuelwood sales. Fifty-two percent of the sellers sell less than 200 kg of fuelwood per month. In the aggregate, from a sample of 4,658 households that do not buy, 2,700 or close to 60%

[28]For example Hanna et al. (2016) report that households in their survey used about 4.5 kg of wood to cook their last meal, roughly in the same ball-park as our daily consumption of slightly more than 6 kg.

[29]For eight households located in Delhi (6) and in Nagaland (2), we are not able to compute the mean collection rate because we only observe one buyer in each state and they do not spend any time collecting.

[30]Our estimates are close to those of the World Bank (2005) which estimates that 40% of India's rural population relies in part on fuelwood for cash income.

[31]In robustness checks reported later, we employ alternative definitions of the seller household, e.g., if collection exceeds consumption by a certain volume.

are sellers.

Travel time to forest as a proxy for forest cover

Finally we check if household travel times to forest are negatively correlated with forest cover. Intuitively we expect a lower stock of forest at the local level will be reflected in longer travel times. We do not observe the identity of individual villages in the IHDS Survey and are thus unable to match them to any granular data, such as satellite-based measures of forest cover. However, we know the districts where the villages are located. We can therefore match household-level data on travel time to district-level forest cover obtained from the Forest Survey of India (FSI) of 2005, the same year as the IHDS Survey.[32] Figure 6 shows forest cover by district in the year 2005 in thousands of square kilometers (Forest Survey of India, 2005). Using the 2001 FSI survey of forest cover, we observe that between 2001 and 2005, 52 of the 215 districts in our sample experienced deforestation: 1,553 households from our sample of 5,563 households live in these districts. Another 900 households live in the 37 districts that experienced afforestation. The remaining 3,110 households live in the 126 districts that saw no change in forest cover during this period.

To investigate the relationship between household travel time and forest cover, we regress travel time to forest on forest cover and the change in forest cover between 2001-2005. To account for differences in forests across states, we employ state-level fixed effects. The results are reported in Table 6.

The first two columns report estimates that control for either forest cover or forest growth, and the third column includes both controls. The estimates are quite similar when controlling for both forest measures. The coefficient estimates for forest cover are negative and statistically significant. That is, travel time is negatively correlated with district-level forest stock. The coefficient estimate in the first row of column (3), -0.96, indicates that a 1000 km^2 increase in forest cover in a given district, just slightly below one standard deviation, is associated with a decrease in household travel times in that district by nearly one minute.[33]

Empirical specification

In order to estimate how travel time to the forest affects outcomes, namely household collection of fuelwood and purchase, sale and consumption, we specify the estimating equation:

[32] From the 5,566 households, three live in a district for which the forest cover information is missing. We are thus able to match 5,563 households to their district forest cover.

[33] The negative relationship between local abundance of forests and travel time has been noted for other countries, such as Nepal (see Baland et al., 2018).

$$y_i = \alpha + \beta \text{travel}_i + X_i \Gamma + \delta_{r(i)} + \varepsilon_i. \tag{7}$$

The variable y_i denotes one of four dependent variables: the time spent collecting fuelwood, or the quantity of fuelwood bought, sold or consumed by household i. The variable $travel_i$ denotes household travel time to the forest, and the parameter β captures the effect that travel time has on collection time, buying, selling, and consuming of fuelwood, which will be clear from the context. The vector X_i contains information on household-specific variables, such as income and the number of persons in the household, and α is a constant; ε_i is the error term.

The term $\delta_{r(i)}$ represents fixed effects, either for the district or the village where the household is located. When we estimate with district fixed effects, we can add village-level variables, namely prices (fuelwood and kerosene) and population.[34] However the estimates may suffer from omitted variable bias because we do not account for differences across villages such as population density, terrain or proximity to markets and demand centers, to the extent that these factors are not built into the prices of fuelwood and its substitute, kerosene. Using village fixed effects controls for all village-level determinants of fuelwood activities including village-level prices.[35]

We discuss three issues with our identification strategy, namely: (1) the use of estimated variables, i.e., the volume of fuelwood sold and consumed; (2) the possible endogeneity of travel time to the forest and; (3) misspecification.

We have estimated fuelwood sales and consumption by households. These variables may suffer from measurement error. Since we use estimated variables as dependent variables in our regressions, the parameters are still consistently estimated though the standard errors may be larger. Nontheless, to evaluate the robustness of the baseline estimates for fuelwood sold, we re-estimate the model with various alternative definitions for seller households, as reported later.

A critical identification assumption is that the travel time to the forest is exogenous. Households may use different modes of transportation than walking, such as cycling or using draft animals. The reported travel time will then be a function of the transport technology

[34]Since prices are reported at the village level, we cannot introduce them in the baseline specification with village fixed effects.

[35]The price of fuelwood could actually be a *bad control*, since it could act as an outcome variable in a regression with travel time, i.e. travel time is likely to be an important determinant of the price of fuelwood. We face the trade-off between having a regression with an omitted variable problem or having a bad control which may bias the estimates. However, since the coefficient on travel time is stable across regressions with village and district level fixed effects, this problem is likely to be small.

adopted. We control for the three most plausible alternatives (to walking) that households may employ: cycling, scooters, and using draft animals. Another concern is that households may choose forest locations based on their status as collectors, i.e., sellers may collect from a different site than those who only consume fuelwood for their domestic energy needs. Their respective choices may be based on the quality of the forest. It is reasonable to expect forests farther away from the village being more dense and yielding higher volumes of fuelwood for the same effort. If sellers systematically choose far-flung locations which are higher yield, then the results should be weaker when we perform the estimation only with sellers (same with buyers, if they consistently choose specific locations distinct from others in the village). As we report below, our results hold when the estimation is done only for these sub-groups in our sample. Finally, households may collect fuelwood from their own land or from open access forests. Below, we use data on forest ownership and find that including property rights over forest land has little impact on our baseline estimates.

If households choose their residence based on distance to the forest, perhaps to minimize the cost of collecting energy, travel time may be endogenous to fuelwood collection and the buying, selling, and consumption of fuelwood. Such residential sorting may invalidate the use of distance as an exogenous determinant of the outcome variables. There are several factors that suggest that residential choice may not be determined by proximity to forests. In general, rural households in India rarely relocate. On average, households have lived in the same dwelling for 83.52 years – 87.7% of the households in our sample report the maximum value (set by the questionnaire) of 90 years, as shown in Figure 2. Thus, the typical household moved into the current village more than 80 years ago, in the 1920s, when forest cover was likely more abundant.

If the forest boundary has receded over time, this could lead to migration out of the village or relocation within the village to a new location. However, out-migration from villages is typically low in India. According to Topalova (2010), most migrants in rural India are women re-locating due to marriage – 40% of women versus only 7% of men reported a change in location in her study. She points out that only 3-4% of rural households changed district or employment within the last 10 years, while an even smaller share (1.6%) of the rural district population migrates to the city. The 2001 Census reports that only 1.6% of all Indian households migrated in 2001, and this figure includes both urban and rural households.[36]

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

Within-village relocation in response to the scarcity of fuelwood may also be limited, mainly because rural real estate markets are essentially non-existent: in 2001, 95.4% of rural households owned their primary residence and this rate has been roughly constant over the previous four decades (Tiwari, 2007). Most homes are built by residents and not bought in the market because of a lack of access to credit markets. Estimates suggest that between 55% and 80% of rural real estate expenditures are spent on home alterations, improvements and major repairs (Tiwari, 2007).

Only 189 of the 5,566 households in our sample (3.4%) changed location within the last 20 years. About 10.9% of households changed location over the last 90 years. Figure A1(a) in the Appendix shows that there is no trend in travel times for households that moved in early years relative to those that moved recently. We also check if households that moved more recently settled in villages closer to towns (see Figure A1(b)). The data do not show such a pattern. Finally, we check if seasonal migration rates are indeed significant in the villages in our sample. Figure A2 shows the share of villages from which workers left for seasonal work during the year. More than 49% of the villages in our sample report less than 20 people leaving annually for seasonal work, while for 43% of the villages, none left for seasonal work. This suggests that seasonal migration is small and unlikely to affect our estimation.

Finally, misspecification may arise since many households do not buy or sell fuelwood, i.e., the conditional mean of the dependent variable may be nonlinear with respect to travel time because of zero-valued observations. Estimating equation (7) by ordinary least squares, our baseline estimation model, may yield inconsistent estimates. We report results from a Tobit model and find that the estimates are quite similar to the baseline OLS estimates.

4 Estimation results

Here we report baseline estimates of the effect of travel time to the forest on the time spent collecting fuelwood, and on volumes bought, sold and consumed by households, as well as results from several robustness checks.

Baseline specification

Table 7 reports estimates from regressing the weekly amount of time a household spends collecting fuelwood on travel time. Column (1) reports results from a simple regression while in column (2) we add household- and village-specific characteristics. In columns (3) and (4) we report results from using district and village fixed effects, respectively. Standard errors are clustered at the district-level in all specifications, and are reported below each coefficient estimate.

The coefficient estimates for travel time are all positive and statistically significant, indicating that travel time increases collection time. In column (1), the estimate equals 0.039 and implies that a 10-minute increase in one-way travel time to the forest increases the time spent in collecting fuelwood by 0.39 hours per week, or about 23 minutes. Column (2) includes household and village controls and yields a coefficient estimate similar to column (1). Column (3) adds district fixed effects, which reduces the coefficient estimate but increases the R^2, suggesting that there is heterogeneity in fuelwood collection time across districts. With village fixed effects, the estimate in column (4) is similar to that in column (3). It equals 0.024, indicating that a 10-minute increase in one-way travel time increases weekly collection time by 0.24 hours, or 14 minutes. That is, since a 10-minute increase in travel time implies a 20 minute increase in the return trip, the estimated effect implies a less than one-for-one increase between total travel and collection time.

The estimates in columns (3) and (4) are derived from specifications that use different fixed effects. The coefficient estimates for travel time are virtually the same: for a 10-minute increase in travel time, the estimates in column (3) and (4) imply increases in weekly collection time that differ by 1.2 minutes. The problem with using district fixed effects is that the specification may be subject to omitted variables bias because of unobserved village-level factors affecting fuelwood collection and energy choices. The village fixed effects control for these unobserved factors; that the estimates do not differ across the specifications suggests that such omitted variables bias is not an issue.

The coefficient estimate for fuelwood price in column (3), 0.104, is statistically significant and indicates that an increase in the fuelwood price of one rupee increases weekly collection time by six minutes. It supports our prediction that as fuelwood becomes more expensive, households devote more time collecting it. Alternatively, a one-standard deviation increase in the fuelwood price, equal to Rs 1.97, increases collection time by about 12 minutes per week or 6% of a standard deviation in collection time. In contrast, by using the travel time coefficient estimate in column (3), 0.026, a one-standard deviation increase in distance, about 32 minutes, increases fuelwood collection by about 50 minutes or 27% of a standard deviation in collection time. This evidence suggests that travel time to forest is a more important determinant of collection time than the price of fuelwood.

From column (4), the coefficient estimate for the logarithm of household income per adult equivalent, −0.056, although not statistically significant, suggests that higher income households spend less time collecting. The coefficient for household size, 0.049, suggests that a household with an additional member spends about three additional minutes each week collecting fuelwood, while the estimate for education, -0.019, indicates that households with an additional year of schooling reduce their weekly collection time by about 1.1 minutes, all else being equal. That is, households that are poorer, greater in size, and less educated – essentially, households with a lower opportunity cost of time – spend more time collecting fuelwood, consistent with our predictions.

Table 8 reports results from estimating equation (7) using the three other dependent variables – quantity bought, sold and consumed by households. We only report the travel time and price coefficient estimates, but all specifications include district or village fixed effects with the same combination of covariates as in the final two columns of Table 7. The statistically significant estimates indicate that travel time to the forest reduces quantity bought and increases quantity sold, thus supporting our model predictions. The estimates in columns (1) and (2), -0.72 and -0.62, indicate that an increase in travel time of 32 minutes, about one-standard deviation, decreases fuelwood bought by 23 and 20 kg/month, respectively. The difference between the two estimates is 3 kg – small relative to mean volume bought of about 40 kg, which again suggests that there may be little omitted variables bias.

The price coefficient estimate, in the first column, is statistically significant and has the predicted sign: a higher fuelwood price reduces the quantity bought, i.e., demand for fuelwood is downward-sloping. The coefficient estimate, -22.14, implies that an increase of one rupee in the price of fuelwood decreases fuelwood purchased by 22 kg per month.

We quantify the relative magnitudes of the cost effect (through travel time) and the price effect by comparing the estimates in column (1). A one-standard deviation increase in the travel time (cost) decreases fuelwood bought by 7% of a standard deviation. However, a one-standard deviation increase in the price of fuelwood decreases the quantity purchased by 13%. Thus the price increase explains nearly twice the variation in the quantity of fuelwood bought compared to the increase in the cost of collection.

Columns (3) and (4) in Table 8 show that travel time has a positive and statistically significant effect on the quantity of fuelwood sold. The district- and village-level coefficient estimates are similar – an additional 32 minutes of travel time causes an increase in the quantity sold by 61 and 66 kg on average, respectively.

The fuelwood price coefficient estimate in column (3) is of the expected sign, suggesting that supply is upward-sloping. Though the magnitude is similar to the price effect on quantity bought, the estimate is not statistically significant; the standard error is relatively large, possibly because the dependent variable is estimated. The coefficient estimate, 23.79, indicates that a one rupee increase in the price of fuelwood increases the monthly quantity sold by a household by about 24 kg on average.

Columns (5) and (6) show that when the dependent variable is quantity consumed by the household, the coefficient estimates are statistically insignificant and small. Travel time to forest does not affect household consumption, consistent with the prediction from our model.

Overall, if we interpret travel time as a proxy for local forest cover, these results suggest that when the forest cover is low, households collect more fuelwood, buy less and sell more, and their consumption is unaffected.

Nonlinear effects of travel time

The baseline regressions above estimated linear effects of travel time on outcomes. We investigate the existence of non-linearities in the marginal effect of travel time by adding a polynomial to (7) and specifying the following equation:

$$y_i = \sum_{k=1}^{K} \beta_k \text{travel}_i^k + X_i \Gamma + \delta_{r(i)} + \varepsilon_i. \tag{8}$$

Taking the partial derivative, the marginal effect of travel time is given by $\sum_{k=1}^{K} k\beta_k \text{travel}_i^{k-1}$. To avoid over-fitting, we use a fifth-degree polynomial, so that $K = 5$.

The estimated marginal effects from estimating (8) using the district-level specification are plotted in Figure 7 with 90% confidence intervals. Panel (a) shows that the marginal effect of travel time on collection time is everywhere positive, but becomes smaller at high values of travel time and becomes statistically insignificant for travel times beyond 100 minutes (recall mean one-way travel time is 38.7 minutes). Panel (b) shows that the effect on quantity bought is non-positive. For values of travel time below 40 minutes, households respond negatively at the margin and buy less fuelwood. For higher values, the effect of travel time is not statistically different from zero. In panel (c) we see that the effect on quantity of fuelwood sold is positive and large at low values of travel time, is close to zero in the interval 40-60 minutes and increases at travel times of 80 minutes or higher. Finally, panel (d) supports our prediction that the effect of travel time on fuelwood consumed is not significant.

Tobit model estimates

Using a Tobit model, we can check whether travel time affects fuelwood collection and buying and selling at the extensive margin (and intensive margin). This check also addresses concerns with zero-valued observations (e.g., 84% of households in our sample do not buy fuelwood) which may induce bias in the OLS specification used earlier. We estimate (7) using a Tobit model and report the results in Table 9. In panel A, we report the coefficient estimates; in panel B, we report the marginal effect of travel time on the outcomes evaluated at the average value for all covariates, which are comparable to the baseline coefficient estimates in Tables 7 and 8; and panel C reports the marginal effect on the probability that a household chooses a positive value for the specified outcome variable. All specifications include district or village fixed effects with the same combination of covariates as in the final two columns of Table 7. Standard errors are clustered at the district-level and reported in parentheses.

For collection time and quantity of fuelwood consumed, the Tobit estimates are roughly similar to baseline estimates, which makes sense since these variables contain few zero-valued observations. For the quantity bought and sold, Tobit estimates are larger. The average marginal effect of travel time on quantity bought is -1.316 and -1.022 in the Tobit model, suggesting that an increase in travel time of 32 minutes (one-standard deviation) reduces the quantity bought by 42 and 33 kg per month, respectively. These effects are large relative to baseline estimates of 23 and 20 kg/month, under district and village fixed effects specifications. For quantity sold, average marginal estimates for the Tobit model suggest a one-standard deviation increase in travel time increases the quantity of fuelwood sold by 52 and 57 kg respectively, compared to baseline estimates of 61 and 66 kg. These results suggest that the estimates are not biased due to misspecification.

In panel C we show that travel time has an extensive margin effect on collecting, buying, and selling of fuelwood. The estimates in the first two columns, both statistically significant and equal to 0.003, indicate that an increase in travel time by one standard deviation, about 32 minutes, increases the probability that a household collects fuelwood by 0.1 or an increase of 11% from the mean probability that a household is a collector. The estimates in the next two columns indicate that increases in travel time decrease the likelihood that a household buys fuelwood. For example, the estimate in column (3), -0.002, implies that a one standard deviation increase in travel time reduces the probability that a household buys fuelwood by 0.06, a decrease of 40% from the mean probability. Columns (5) and (6) suggest that travel time increases the probability that households sell fuelwood. In particular, the estimate in column (6) implies that a standard deviation increase in travel time increases the probability that a household is a seller of fuelwood by 20% from the mean. Finally, the estimates in the final two columns suggest that travel time has no effect on the probability that a household consumes fuelwood.

These results show that an increase in travel time not only increases the quantity of fuelwood collected and sold, but it also increases the probability that a household collects and is a seller. That is, in regions with low forest cover, aggregate volumes collected and sold are likely to be higher.

Additional robustness checks

We perform several additional robustness checks. First, we re-run the estimation based on alternative definitions of a seller household and then on the sub-sample of sellers. We next consider whether property rights over forests affects our empirical results.

Alternative definitions of a seller household

Until now, a household is classified as a seller if and only if their fuelwood collection exceeds consumption. It may be the case that households store fuelwood and did not report it in the survey, in which case we may be overstating the quantity of fuelwood sold. Here, we check whether using more stringent definitions of the quantity of fuelwood sold affects our results. We characterize a household as a seller only if its collection net of consumption exceeds the 25th, 50th, and 75th percentiles of the distribution of the difference between quantity collected and sold. That is, the definition is increasingly stringent with a larger gap between collection and consumption and results in a fewer numbers of seller households, as reported in Table 10. All specifications include the same set of controls as before and are comparable to the coefficient estimates in columns (3) and (4) of Table 8.

The estimates are quite similar for all the definitions of seller households. The more restrictive the definition of a seller, the smaller are the coefficient estimates because more households fall into the category of non-sellers. Recall that the coefficient estimates for the baseline (Table 8) were 1.92 and 2.06 for district and village specifications, respectively, which are quite similar to the 25th percentile coefficient estimates shown here. For the most restrictive definition of seller, the coefficient estimate of 1.89 in column (6) implies that a 32 minute increase (one standard deviation) in travel time increases the quantity of fuelwood sold per month by about 61 kg on average, relative to 66 kg for the baseline estimation in Table 8. Overall, the estimates suggest that the results are robust to the definition of seller households.

Estimation with the sub-sample of seller households

A critical identification assumption is that the travel time to the forest is exogenous. One concern we described above is that households may choose forest locations based on their status as sellers, and sellers may collect from different sites, perhaps due to higher forest quality (e.g., more dense forests located farther away from the village) than those who only collect fuelwood for their domestic energy needs. If sellers systematically choose a different set of locations than those who collect for personal use, then our findings should disappear when we perform the estimation only with sellers.

Using only the sub-sample of seller households, we exclude households who do not sell, hence the estimates will only reflect the intensive margin effect of travel time on the quantity of fuelwood sold, shown in Table 11 for both district and village fixed effects. The estimate in column (1), 2.424, is statistically significant and indicates that larger travel times lead to an increase in the volume sold. The estimate in column (2) shows a similar larger effect. The estimates in both columns are larger than the baseline estimates in columns (3) and (4) of Table 8, since we have excluded households that do not sell fuelwood. These results suggest that our intensive margin results are not due to differential forest targeting by sellers and non-sellers.

Fuelwood collection from private and public forests

In the IHDS survey, households are asked whether they purchase fuelwood, collect it from their own land, from publicly-owned land, or a combination of the two. Here we re-estimate our baseline model specification using sub-samples of households that obtain fuelwood from privately-owned land, from public lands, and from both.[37] In Table 12, each panel corresponds to a different dependent variable.[38] All specifications use the full set of controls and either district or village fixed effects.[39]

Panel A reports estimates of the effect of travel time on collection time. For households collecting from privately owned forests, the estimates from the district-level specification, 0.022 and village-level specification, 0.020, are similar to the baseline estimates in Table 7

[37]The total number of such households does not add up to our full sample of 5,566 because of non-response by several households.

[38]Since many households reported purchasing fuelwood, we do not know if that fuelwood was sourced from public or private lands. We are not able to perform this estimation on volumes bought. Moreover, there are no households that sell fuelwood and collect it both from own as well as public lands.

[39]Note that households who collect from private lands tend to be richer than those collecting from open access forests. Our regressions control for household income.

of 0.024 and 0.026, respectively. The estimates in columns (3) and (4), from the subsample of households collecting from the commons, are a bit lower in magnitude, although still statistically significant. For households that collect from both types of forests, in columns (5) and (6), the estimates are again similar to baseline [40]

The estimates for collection from private and publicly-owned land are similar when the dependent variable is fuelwood sold (Panel B). The coefficients in the first four columns of Panel B are all statistically significant and similar in magnitude to the baseline estimates reported earlier – 1.92 and 2.06 for district and village fixed effects. There are no sellers who collect from both private and public forests. Finally, all the estimates for consumption are small and statistically insignificant, as before.

5 Estimating excess supply of fuelwood to nearby towns

Our results suggest that higher travel times increase fuelwood collection and sales, and reduce purchase, both at the intensive and extensive margins. However, travel times have no significant effect on consumption. This begs the question: where is this excess fuelwood collected at the village level being consumed? Given its low value to volume ratio, large quantities are unlikely to be exported. Casual empirical evidence suggests that the excess supply is likely consumed by the poor in nearby towns and cities (Farsi et al., 2007). We can use our estimates on collection and consumption to quantify this leakage and its contribution to particulate emissions in cities.

For each state, we know the share of rural households collecting and consuming fuelwood and the average size of these households from the IHDS survey. Multiplying by the state population (from the 2001 Census) gives the number of households collecting and consuming fuelwood. Using the mean monthly volume of fuelwood collected and consumed, we aggregate to obtain monthly volumes by state.

As an illustration, consider the state of Maharashtra. Our sub-sample from the state suggests that about 68.5% of rural households collect fuelwood, and the average household size is 5.4 members. The IHDS survey is based on the 2001 Census which gives a total state population of about 112.4 million, of which 54.78% live in rural areas, resulting in

[40]Households that collect from private forests have lower travel times than those collecting from public lands (sample means are 38 and 46 minutes, respectively). This makes sense since households may collect from plots they or their neighbors own. They also spend less time collecting from private forests: 3.02 hours/week vs 3.30 hours/week for public forests. So both travel and collection times are greater for public forests. The non-linear effects shown earlier in Figure 7 suggest that the estimated marginal effect of travel time on collection time declines rapidly, which we see in our estimates.

a total rural population of 61.56 million. This yields 7.8 million households that collect fuelwood in rural Maharashtra. We multiply this number by the average fuelwood collected by households in Maharashtra, which is 260 kg/month.[41]

Multiplying this quantity by twelve yields an estimate of the aggregate annual quantity of fuelwood collected in rural Maharashtra, which is 24.3 million tons. This procedure is replicated for all other states.[42] Aggregating over all states yields the annual volume of fuelwood collected at 228.1 million tons.[43] Our estimates are close to Government of India (GOI) figures for total fuelwood consumed nationally – about 5% higher than the GOI figure of 216.4 tons.[44]

If we assume that this fuelwood has a standard 20% moisture content, the volume collected equals 1.45 million barrels per day of crude oil in terms of energy content.[45] This aggregation procedure can be repeated with our consumption estimates, to yield an annual rural consumption of 185.1 million tons. The excess supply (collection net of rural consumption) of 43 million tons is not consumed in rural areas.[46] Some fuelwood is used along highways mainly for cooking in restaurants called *dhabas*, which we roughly estimate at 2.5 million tons.[47]

The volume of fuelwood which leaks into nearby towns and cities can thus be approximated as 40.5 million tons or about 17.8% of total fuelwood collected. According to Grieshop et al. (2011), each kg of dry fuelwood burned generates on average 410.3 grams of CO_2 and

[41] To reduce the impact of outliers, mean collection and consumption are computed after excluding the top 5% values of the distribution.

[42] Because of similarities and in order to have a sufficient number of households in each state, we merge a few small states with their larger neighbors: Gujarat with Daman & Diu and Dadra & Nagar Haveli; Karnataka with Goa; Uttaranchal with Himachal Pradesh; Delhi with Haryana; Sikkim with West Bengal; Arunachal Pradesh with Meghalaya, Assam, Nagaland, Manipur, Tripura and Mizoram and Pondicherry with Tamil Nadu.

[43] Ideally, this aggregation should be performed at a more granular level, such as district, to capture the heterogeneity within states in forest cover, geography and population. However, our survey contains data only for 266 of the 640 districts, so we would have to use state averages for the remaining. In some districts all the households interviewed were fuelwood sellers, so taking their collection rates may lead to overestimation.

[44] See https://data.gov.in/catalog/annual-fuel-wood-consumption.

[45] India consumes 3.5 mbpd of crude oil. So the size of the fuelwood market is more than 40% of national crude oil consumption.

[46] We make the reasonable assumption that no fuelwood is collected within cities.

[47] According to the National Institution for Transforming India (Government of India), in 2005, India had about 65,569 kilometers of national highways (http://www.niti.gov.in/content/length-national-highway-sq-km). It is difficult to get figures for how many dhabas exist on these highways but suppose we assume that there is one dhaba every kilometer of highway. That makes for 65,569 *dhabas*. In reality, there may be more along major highways and fewer in remote areas. Singh et al. (2010) estimates that dhabas consume about 105 kg of fuelwood per day. These numbers result in a yearly consumption by dhabas of 2.5 million tons of fuelwood.

4.2 grams of $PM_{2.5}$. Thus if all the excess fuelwood is used for cooking and heating, this leads to an annual CO_2 load of 13.3 million tons and 0.14 million tons of $PM_{2.5}$, only in urban areas. If this fuelwood is replaced by kerosene, and taking stove efficiency for fuelwood as 26.5% and for a kerosene stove at 50%, the CO_2 generated would reduce to 5.84 million tons but $PM_{2.5}$ would decline to 3.54 thousand tons, a reduction of about 97%. A complete switch from fuelwood to LPG would lead to similar reductions for the two pollutants.[48]

Where is this excess supply consumed? We try two approaches. First we distribute this leaked fuelwood among the 46 cities with population exceeding one million. Alternatively, recognizing that the bulk of urban fuelwood is consumed by people living in slums and squatter settlements, we can apportion the leaked fuelwood by slum population for these cities. The two methods yield similar results for most cities. As an example, if we use total population, Delhi receives 12.9 thousand tons of the $PM_{2.5}$ generated by the excess supply of fuelwood. Using the slum population figures, it receives 8.8 thousand tons annually. According to Guttikunda and Calori (2013), the city of Delhi typically emits a total of 175 tons of $PM_{2.5}$ per day. Thus our estimates suggest that fuelwood accounts for 24-35 tons of $PM_{2.5}$ per day, about 14-20% of the daily ppm load for Delhi.[49]

Finally, we estimate the effect of an exogenous change in forest cover on the excess supply of fuelwood. Suppose forest cover decreases across the board by 10%.[50] If the fuelwood collection rate is assumed to remain unchanged (reasonable if forests recede into the distance but density is unaffected), the effect on collection is given by the coefficient 0.024 in Table 7. Figure 8 shows the aggregate effect of this 10% decrease in forest cover: an increase of 0.52% in quantity collected, and a rise in excess supply of 2.74% and a mean increase of 3% in $PM_{2.5}$ concentrations.[51]

[48]Detailed computations are available from the authors.

[49]Mumbai has a much bigger share of population living in slums resulting in a bigger gap between our two estimates, with a range of 40-77 tons of $PM_{2.5}$ per day. We did a robustness check with the 92 cities with more than 500,000 inhabitants. The estimated $PM_{2.5}$ load for Delhi and Mumbai decrease, but only by a modest amount. In this case, the corresponding range is 20-28 tons per day for Delhi and 31-63 tons for Mumbai.

[50]The coefficient -0.93 in Table 6 suggests that this is equivalent to an increase in travel time of roughly two standard deviations.

[51]The figure also shows the effect of a 20% decrease. The percent increase in excess supply is higher because it is net of consumption which does not change appreciably. The proportional increase in $PM_{2.5}$ is higher because we net out highway consumption.

6 Concluding remarks

Many poor people in developing countries use fuelwood to meet their cooking and heating needs. Households collect fuelwood from neighboring forests and buy and sell it in local markets. Significant volumes of fuelwood are shipped to nearby towns and cities for use, especially in low-income neighborhoods and slums where residents are unable to access cleaner substitutes such as LPG. This paper is the first to examine the causal effect of travel time (to the forest) on the behavior of households that collect, buy and sell fuelwood. We show that higher travel times result in increased collection and sales, as well as a reduction in volumes purchased by households. We quantify the effect of an increase in the fixed costs of collecting by specifying a model with village fixed effects and examine the effect of village-level fuelwood prices using district fixed effects.

We use our estimates for fuelwood collection and consumption to show that in terms of energy content, the volume of fuelwood collected roughly equals 1.45 million barrels of crude oil per day, about a third of India's total consumption of crude oil. About a fifth of this fuelwood collected is not accounted for by rural consumption, and is likely shipped to nearby towns and cities. By our estimates, burning this leaked fuelwood contributes to an additional 18-25 $\mu g/m^3$ of $PM_{2.5}$ concentration in the city of New Delhi. We show that an exogenous decrease in forest cover of 10% will lead to an increase in the excess supply of fuelwood by 2.74% and an increase in urban $PM_{2.5}$ concentrations of about 3%.

These results have a central role in the larger debate on whether developing countries should continue to subsidize cleaner fuels like LPG which is a substitute for fuelwood in cooking. While removing subsidies on LPG and kerosene may reduce fiscal deficits, this may trigger increased consumption of fuelwood, especially by poor households, leading to a net increase in CO_2 and $PM_{2.5}$ emissions.

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Figures

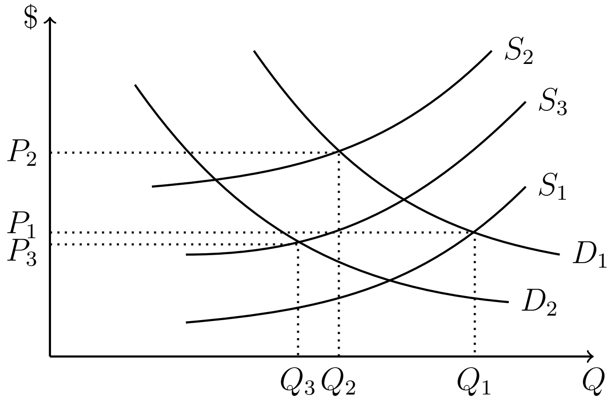


Figure 1: The effect of travel time on fuelwood price and quantity. The supply curves S_1 and S_2 represent villages with low and high travel times, respectively. A higher price of fuelwood P_2 induces more supply, which shifts supply down to S_3. High prices also lead to an inward shift in demand from D_1 to D_2.

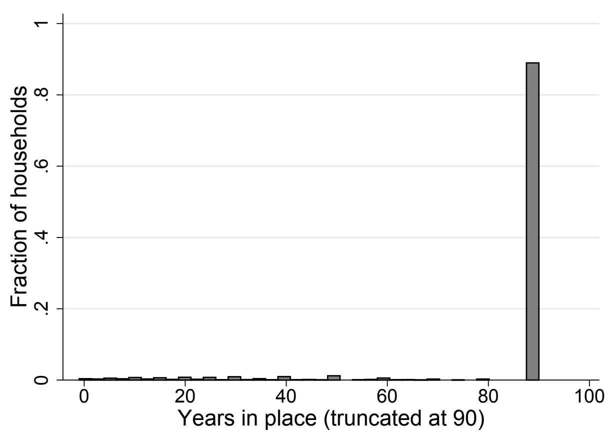


Figure 2: Histogram of years household is at current location (truncated at 90 years)

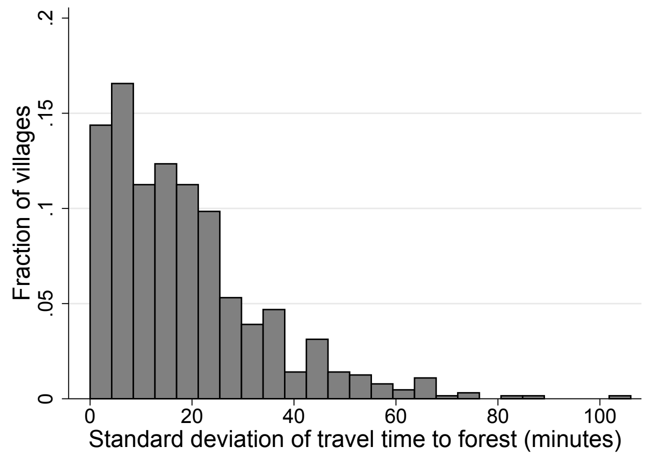


Figure 3: Histogram of village-level standard deviation of travel time to forest

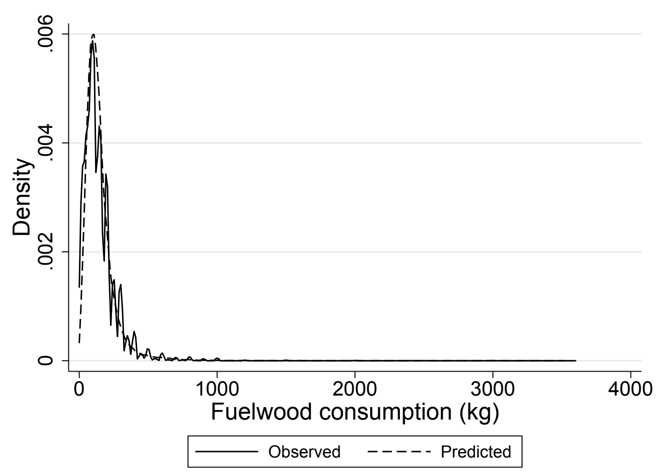
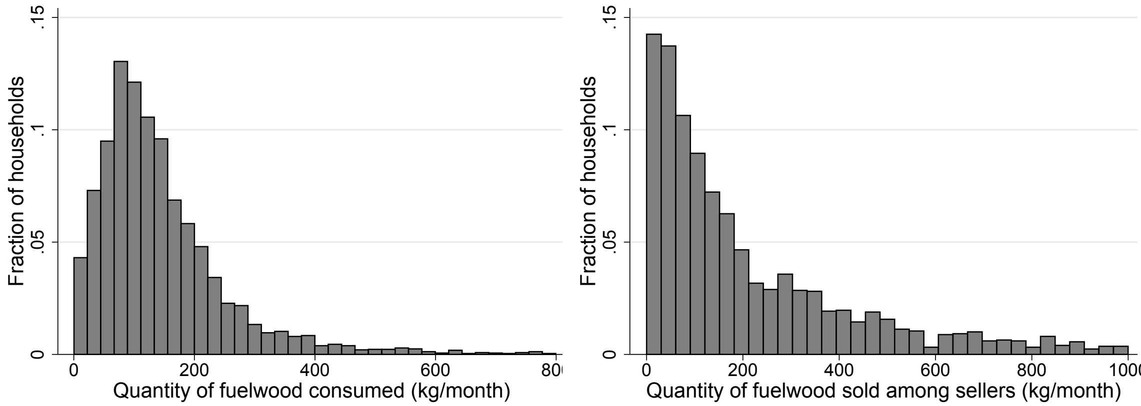


Figure 4: Distribution of observed versus predicted fuelwood consumption in NSS data



(a) (b)

Figure 5: Predicted quantity of fuelwood consumption and sales for IHDS households. (a) Histogram of household consumption of fuelwood (kg/month). (b) Histogram of household sales of fuelwood (kg/month).

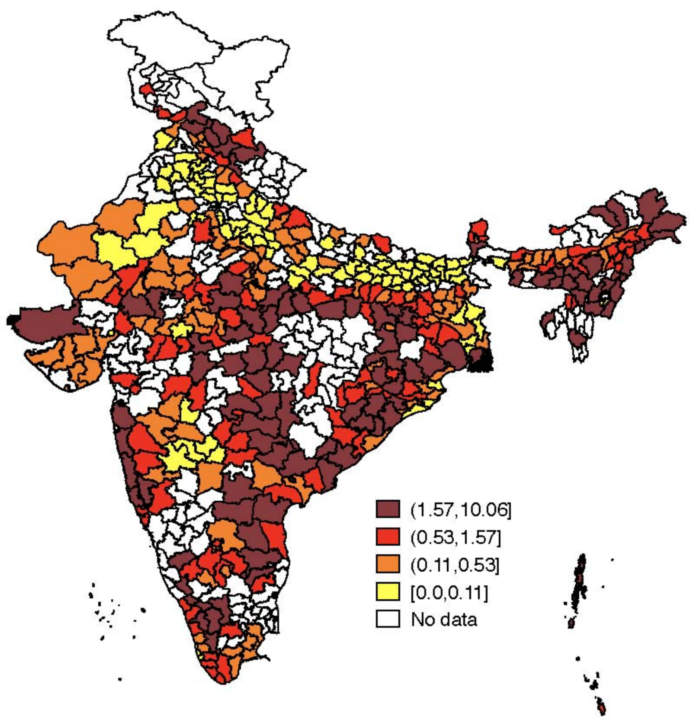
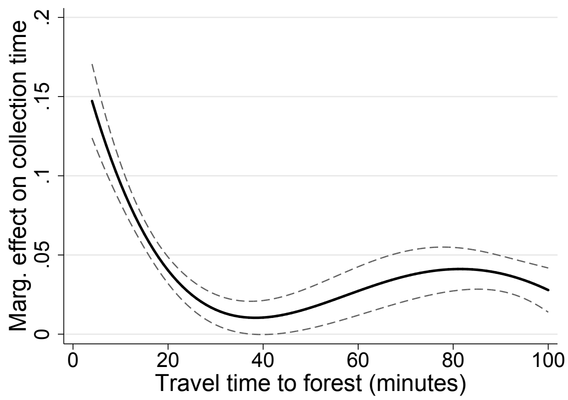
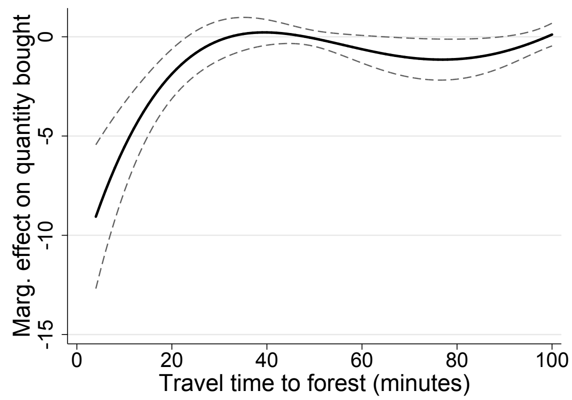


Figure 6: Forest cover in Indian districts in 10^3 square km.

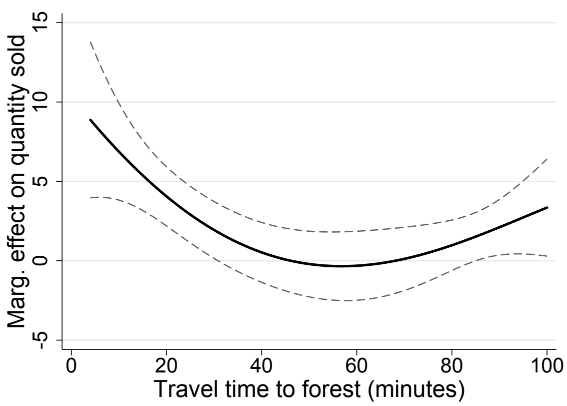
Notes: Figure shows absolute forest cover in districts by quartile. Data are from the Forest Survey of India 2005. Out of a total of 605 districts, data is only available for 407 of them.



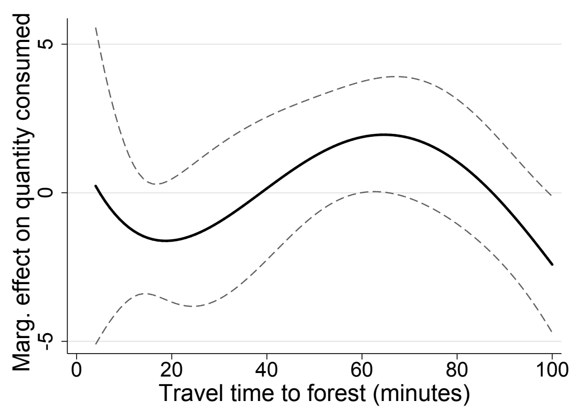
(a) Collection time



(b) Quantity of fuelwood bought



(c) Quantity of fuelwood sold



(d) Quantity of fuelwood consumed

Figure 7: Estimates of the marginal effect of travel time to forest by dependent variable

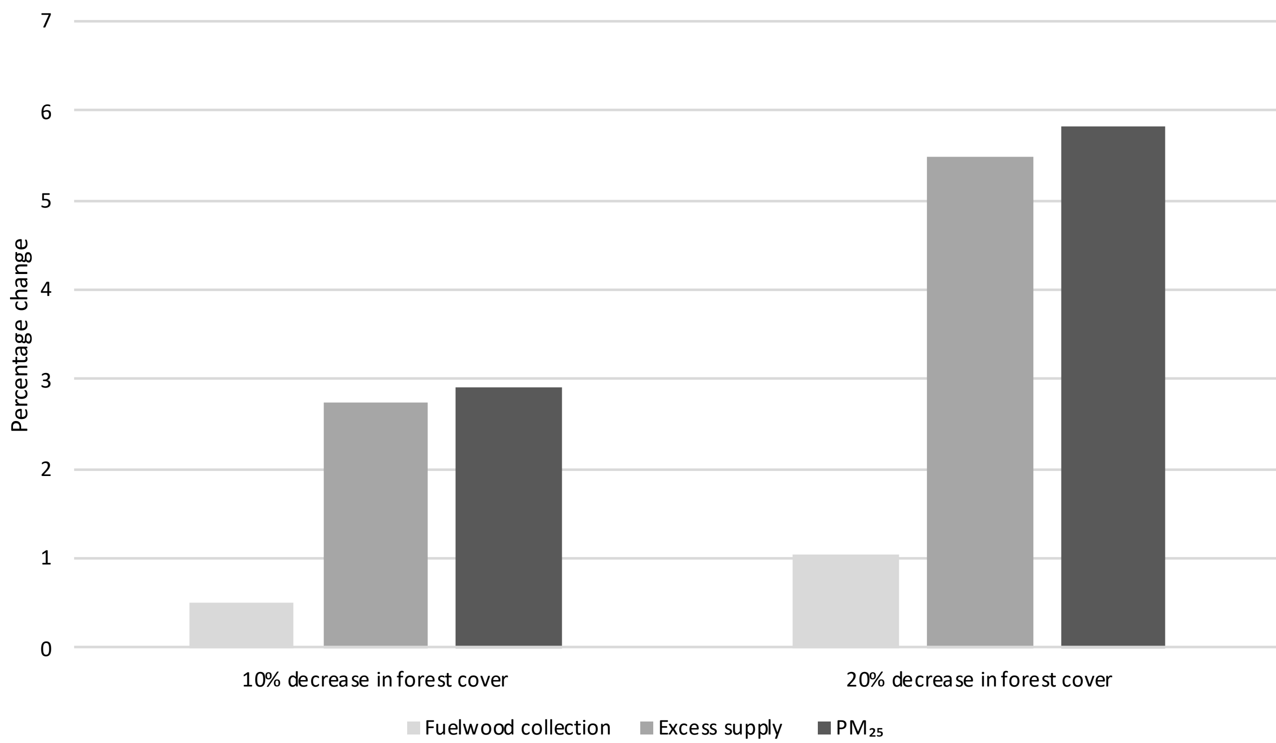


Figure 8: Effect of a decrease in forest cover on fuelwood collection, excess supply and pollution

Notes: A 10% reduction in forest cover is equivalent to a two standard deviation increase in travel time. This leads to 0.52% increase in collection, and 2.74% increase in excess supply and particulate pollution.

Tables

Table 1: Summary statistics, by travel time to forest

	Travel time to forest (minutes):			
	Travel< 25	25 ≤Travel< 50	Travel≥ 50	Total
Travel time to forest (min)	9.48	32.42	75.00	38.70
	(7.87)	(4.87)	(29.26)	(32.24)
Time spent collecting fuelwood (hrs/wk)	1.36	2.95	4.22	2.83
	(1.83)	(2.33)	(4.12)	(3.14)
Fuelwood bought (kg/month)	75.65	29.80	12.66	39.50
	(299.98)	(482.06)	(75.46)	(333.53)
Annual income per adult (1000 Rs)	15.93	13.88	11.29	13.71
	(25.45)	(21.33)	(15.59)	(21.29)
Household size	5.46	5.34	5.44	5.41
	(2.64)	(2.49)	(2.65)	(2.59)
Education of household head (years)	4.59	3.89	3.33	3.94
	(4.52)	(4.25)	(3.96)	(4.28)
Years in current home	81.83	84.76	83.96	83.52
	(21.91)	(17.72)	(18.90)	(19.62)
Household below poverty line†	0.20	0.19	0.27	0.22
	(0.40)	(0.39)	(0.44)	(0.41)
Moved from other state/country†	0.03	0.01	0.01	0.01
	(0.17)	(0.07)	(0.10)	(0.12)
Own bicycle†	0.57	0.48	0.48	0.51
	(0.50)	(0.50)	(0.50)	(0.50)
Own motorcycle/scooter†	0.15	0.11	0.07	0.11
	(0.35)	(0.31)	(0.25)	(0.31)
Own draft animal†	0.56	0.53	0.56	0.55
	(0.50)	(0.50)	(0.50)	(0.50)
Hindu religion†	0.86	0.89	0.92	0.89
	(0.34)	(0.32)	(0.27)	(0.31)
Brahmin caste†	0.03	0.02	0.02	0.02
	(0.18)	(0.13)	(0.13)	(0.15)
Other backward caste†	0.45	0.43	0.40	0.43
	(0.50)	(0.50)	(0.49)	(0.49)
Scheduled tribe/caste†	0.28	0.34	0.40	0.34
	(0.45)	(0.47)	(0.49)	(0.47)
Reported conflict in village†	0.41	0.41	0.41	0.41
	(0.49)	(0.49)	(0.49)	(0.49)
Observations	1859	1884	1784	5566

Notes: † denotes indicator variables. Rs = Indian Rupees; min = minutes; hrs = hours; wk = week. Income is measured as total annual household income per adult equivalent. Household size is the number of persons living in the house. Households are located in one of 733 villages and 214 districts.

Table 2: Summary statistics for village variables, by travel time to forest

	Travel time to forest (minutes):			
	Travel< 25	$25 \leq$Travel< 50	Travel≥ 50	Total
Price of fuelwood (Rs/kg)	1.65	1.73	1.40	1.60
	(2.51)	(1.94)	(1.08)	(1.97)
Price of kerosene (Rs/liter)	15.55	14.70	15.51	15.25
	(4.27)	(3.75)	(3.49)	(3.88)
Live in village with population below 1000†	0.22	0.25	0.28	0.25
	(0.41)	(0.43)	(0.45)	(0.43)
Live in village with population 1001-5000†	0.53	0.65	0.62	0.60
	(0.50)	(0.48)	(0.49)	(0.49)
Live in village with population above 5000†	0.25	0.10	0.10	0.15
	(0.43)	(0.30)	(0.31)	(0.36)
Observations	1719	1689	1498	4940

Notes: Notes: † denotes indicator variables. Rs denotes Indian Rupees. Households are located in one of 636 villages and 203 districts.

Table 3: Descriptive statistics for NSS and IHDS households

Variable	NSS	IHDS
Household with male head†	0.89	0.91
	(0.31)	(0.29)
Head of household illiterate†	0.48	0.44
	(0.50)	(0.50)
Head of household finished school†	0.02	0.07
	(0.14)	(0.26)
Self-employed†	0.53	0.65
	(0.50)	(0.48)
Own their home†	0.99	0.97
	(0.11)	(0.17)
Hindu religion†	0.85	0.89
	(0.35)	(0.31)
Own ration card†	0.85	0.86
	(0.36)	(0.35)
Household size	5.02	5.34
	(2.42)	(2.53)
Household members older than 15 years†	0.69	0.72
	(0.23)	(0.22)
Age of head of household	45.63	47.62
	(13.36)	(13.42)
Land owned (hectares)	0.86	1.03
	(7.33)	(2.14)
Consumption of electricity (Rs/month)	51.93	85.03
	(74.81)	(156.00)
Consumption of dung (Rs/month)	29.21	2.48
	(53.35)	(19.64)
Consumption of kerosene (Rs/month)	35.90	34.89
	(27.21)	(29.45)
Consumption of LPG (Rs/month)	12.56	33.14
	(50.60)	(88.26)
Consumption of meat (Rs/month)	92.07	115.91
	(162.98)	(165.49)
Consumption of cereals (Rs/month)	501.81	520.49
	(300.06)	(356.93)
Consumption of salt and spices (Rs/month)	58.84	82.90
	(36.95)	(73.42)
Observations	65386	7306
Districts	572	240

Notes: IHDS and NSS households include only those living in rural areas and consume fuelwood. Sample mean with standard deviation are in parentheses. † denotes indicator variables. LPG is liquefied petroleum gas. Rs is Indian Rupees. In both surveys, self-employed includes non-agricultural and agricultural activities; ration card includes all cards (Antodaya, BPL or other); land owned includes land leased out but excludes land leased in; cereal consumption includes all cereals such as rice and wheat. The NSS survey has 124,644 households which yield data on 65,386 households after taking out those with missing observations. The IHDS observations decreased from 10,169 to 7306 after keeping only those households that consume fuelwood.

Table 4: Observed versus predicted fuelwood consumption

	Mean	Minimum	Maximum	Observations
	A. NSS data			
Observed consumption (kg/month)	122.56	0.25	8100.00	64,667
	(99.44)			
Predicted consumption (kg/month)	123.03	0.03	4839.98	64,667
	(80.23)			
	B. IHDS data			
Predicted consumption (kg/month)	181.05	0.00	9521.26	5,566
	(748.72)			

Notes: Predicted NSS fuelwood consumption is based on estimating equation (5) by district. Predicted IHDS fuelwood consumption is based on equation (6).

Table 5: Summary statistics of dependent variables, by travel time to forest

	Travel time to forest (minutes):			
	Travel< 25	25 ≤Travel< 50	Travel≥ 50	Total
Fuelwood collection (hours/week)	1.36	2.95	4.22	2.83
	(1.83)	(2.33)	(4.12)	(3.14)
Fuelwood bought (kg/month)	75.65	29.80	12.66	39.50
	(299.98)	(482.06)	(75.46)	(333.53)
Fuelwood sold (kg/month)	112.79	139.50	253.17	167.81
	(471.60)	(367.57)	(626.46)	(502.13)
Fuelwood consumed (kg/month)	208.76	154.00	180.75	181.05
	(946.40)	(285.37)	(844.46)	(748.72)
Collectors	1290	1871	1791	4968
Buyers	593	176	135	908
Sellers	603	996	1083	2700
Observations	1859	1884	1784	5566

Notes: Households are located in one of 733 villages and 214 districts.

Table 6: District forest cover and travel time of households to forest

	(1)	(2)	(3)
Forest cover (1000 km^2)	-0.96^{***}		-0.93^{***}
	(0.33)		(0.33)
Growth rate in forest cover, 2002-2004		-0.51	-0.45
		(0.33)	(0.33)
State FE	Y	Y	Y
R^2	0.15	0.14	0.15
Observations	5563	5563	5563

Notes: The dependent variable is one-way distance from house to forest in minutes. Standard errors are in parentheses. *, **, and *** denote estimates statistically different from zero at the 10%, 5%, and 1% significance levels.

Table 7: The effect of travel time to forest on time spent collecting fuelwood

	(1)	(2)	(3)	(4)
Travel time to forest	0.039***	0.039***	0.026***	0.024***
	(0.004)	(0.005)	(0.003)	(0.003)
Log(annual income per adult)		0.033	-0.096**	-0.056
		(0.063)	(0.043)	(0.035)
Household below poverty line		0.352	0.208*	0.129
		(0.298)	(0.108)	(0.112)
Household size		0.046	0.051***	0.049***
		(0.029)	(0.019)	(0.018)
Education of household head		-0.022**	-0.020**	-0.019**
		(0.011)	(0.008)	(0.007)
Years in current home		0.003	-0.001	-0.001
		(0.003)	(0.002)	(0.001)
Moved from other state/country		0.118	0.026	-0.044
		(0.468)	(0.162)	(0.151)
Own bicycle		-0.150	0.002	-0.002
		(0.233)	(0.068)	(0.063)
Own motorcycle/scooter		-0.294*	-0.022	-0.057
		(0.151)	(0.114)	(0.096)
Own draft animal		0.161	0.036	-0.026
		(0.110)	(0.065)	(0.059)
Hindu religion		0.183	0.031	0.116
		(0.211)	(0.120)	(0.099)
Brahmin caste		1.158	-0.246	-0.307
		(0.723)	(0.339)	(0.349)
Other backward caste		-0.091	0.081	0.051
		(0.221)	(0.113)	(0.116)
Scheduled tribe/caste		-0.100	-0.042	-0.046
		(0.179)	(0.116)	(0.116)
Reported conflict in village		-0.061	0.092	0.111
		(0.211)	(0.156)	(0.153)
Price of fuelwood		0.016	0.104**	
		(0.027)	(0.048)	
Price of kerosene		-0.056**	-0.009	
		(0.025)	(0.024)	
Village population (1001-5000)		-0.863**	-0.145	
		(0.372)	(0.161)	
Village population (above 5000)		-1.432***	-0.304	
		(0.383)	(0.207)	
District FE	N	N	Y	N
Village FE	N	N	N	Y
R^2	0.16	0.19	0.59	0.68
Observations	5566	4940	4940	5566

Notes: The dependent variable is the number of hours per week the household spends collecting fuelwood. Robust standard errors, clustered by district, in parentheses. *, **, and *** denote estimates statistically different from zero at the 10%, 5%, and 1% significance levels.

Table 8: Estimates of the effect of travel time to forest on buying, selling, and consumption of fuelwood by households

	Dependent variable:					
	Quantity bought		Quantity sold		Quantity consumed	
	(1)	(2)	(3)	(4)	(5)	(6)
Travel time	-0.72***	-0.62***	1.92***	2.06***	0.07	0.20
	(0.22)	(0.20)	(0.40)	(0.49)	(0.48)	(0.41)
Fuelwood price	-22.14**		23.79		3.95	
	(10.08)		(17.19)		(7.95)	
R^2	0.09	0.27	0.50	0.63	0.18	0.26
District FE	Y	N	Y	N	Y	N
Village FE	N	Y	N	Y	N	Y
Observations	4940	5566	4940	5566	4940	5566

Notes: The dependent variable for each regression is specified at the top of each column. All dependent variables are in kilograms per month. Robust standard errors clustered by district in parentheses. *, **, and *** denote estimates statistically different from zero at the 10%, 5%, and 1% significance levels.

Table 9: Robustness: Tobit estimation

	Dependent variable:							
	Collection time		Quantity bought		Quantity sold		Quantity consumed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Coefficient estimates							
Travel time	0.033***	0.031***	-9.315***	-8.646***	4.514***	4.626***	0.519	0.450
	(0.004)	(0.004)	(2.989)	(2.723)	(0.920)	(0.873)	(0.546)	(0.465)
	B. Average marginal effect estimates							
Travel time	0.026***	0.025***	-1.316***	-1.022***	1.629***	1.770***	0.284	0.247
	(0.003)	(0.003)	(0.364)	(0.281)	(0.278)	(0.289)	(0.297)	(0.252)
	C. Average extensive margin effect estimates							
Travel time	0.003***	0.003***	-0.002***	-0.001***	0.002***	0.003***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
District FE	Y	N	Y	N	Y	N	Y	N
Village FE	N	Y	N	Y	N	Y	N	Y
Zero-valued observations	560	598	4032	4658	2665	2866	564	596
Observations	4940	5566	4940	5566	4940	5566	4940	5566

Notes: The dependent variable for each regression is specified at the top of each column. Collection time is in hours per week, while quantity bought, sold, and consumed are in kilograms per month. All specifications include household controls. Standard errors, adjusted for clustering by district, are in parentheses. *, **, and *** denote estimates statistically different from zero at the 10%, 5%, and 1% significance levels.

Table 10: Robustness: Alternative definitions of seller households

	Household fuelwood collection net of consumption exceeds:					
	25th percentile		50th percentile		75th percentile	
	(1)	(2)	(3)	(4)	(5)	(6)
Travel time	1.91***	2.05***	1.87***	2.01***	1.76***	1.89***
	(0.41)	(0.49)	(0.41)	(0.50)	(0.40)	(0.49)
District FE	Y	N	Y	N	Y	N
Village FE	N	Y	N	Y	N	Y
Number of sellers	1649	2025	1050	1350	504	675
Observations	4940	5566	4940	5566	4940	5566

Notes: The dependent variable is the quantity of fuelwood sold by the household, in kilograms per month. Sellers are defined as households who collect more than they consume. In column 1, a household is defined as a seller if collection exceeds consumption by 58.63 kg/month (25th percentile); in column 2, by 149.22 kg/month (50th percentile); and in column 3, by 366.4 kg/month (75th percentile). Robust standard errors, clustered by district, in parentheses. *, **, and *** denote estimates statistically different from zero at the 10%, 5%, and 1% significance levels.

Table 11: Robustness: Estimation with subsample of households who sell fuelwood

	(1)	(2)
Travel time	2.424***	3.109***
	(0.505)	(0.787)
District FE	Y	N
Village FE	N	Y
Observations	2275	2700

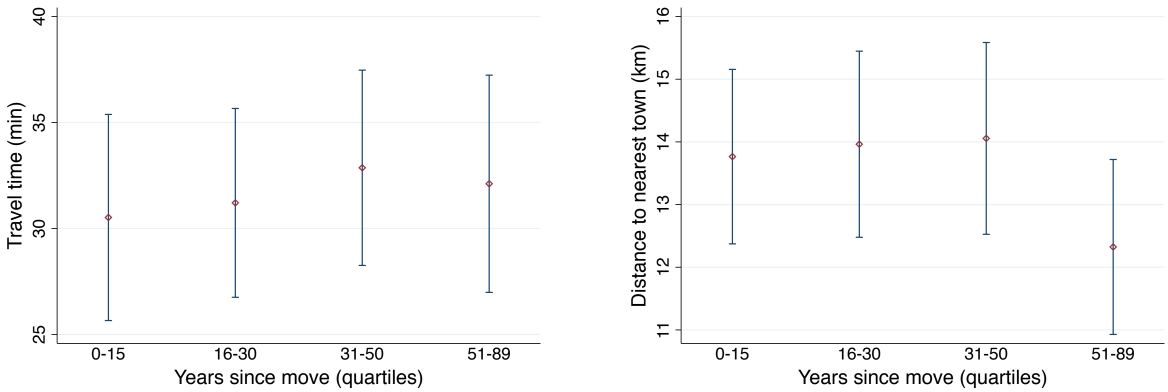
Notes: The dependent variable is the quantity of fuelwood sold by the household, in kilograms per month. Sellers are defined as households who collect more than they consume. Robust standard errors, clustered by district, in parentheses. *, **, and *** denote estimates statistically different from zero at the 10%, 5%, and 1% significance levels.

Table 12: Robustness: Collection from private and public lands

	Fuelwood source:					
	Own land		Public land		Both	
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Dependent variable: collection time					
Travel time	0.022***	0.020***	0.018***	0.017***	0.019***	0.017***
	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)
	B. Dependent variable: quantity of fuelwood sold					
Travel time	1.89***	1.67***	1.42***	2.01**	0.00	0.00
	(0.55)	(0.56)	(0.53)	(0.86)	(.)	(.)
	C. Dependent variable: quantity of fuelwood consumed					
Travel time	-0.13	-0.35	0.03	0.17	2.47	5.26
	(0.70)	(0.81)	(0.15)	(0.16)	(3.34)	(5.03)
District FE	Y	N	Y	N	Y	N
Village FE	N	Y	N	Y	N	Y
Observations	1800	2048	2120	2473	437	437

Notes: The dependent variable is specified at the top of each panel. All specifications use household and village controls along with district-level fixed effects. Robust standard errors, adjusted for clustering by district, in parentheses. For buyers, we are not able to tell if the fuelwood they bought comes from public or private lands. *, **, and *** denote estimates statistically different from zero at the 10%, 5%, and 1% significance levels.

Appendix



(a) (b)

Figure A1: (a) Average time to forest for households that moved over the last 90 years (b) Average distance to the nearest town for households that moved over the last 90 years. In both cases, data are divided in quartiles (11% of the sample reported moving, i.e. 612 households)

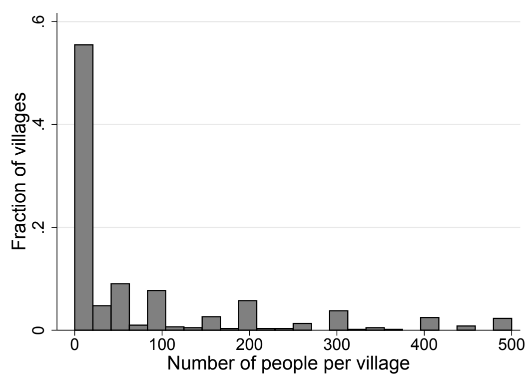


Figure A2: Number of people who left village for seasonal work

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