Research Paper

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Can increased spatial integration lower economic slack and increase wage employment outside the household? Prior literature has suggested that workers turn to self-employment when there is labor rationing. Using data from a time use survey and exploiting variation in connectivity across space stemming from a national rural road building program in India, I find that labor markets with a greater share of the population exposed to roads spend about an hour less in a normal day working on paid employment, primarily wage employment, which is offset by an increase in time spent on production of goods for own use. I discuss potential explanations for this finding.

1. Introduction

Can increased spatial integration lower economic slack? Prior research has shown that village labor markets in India exhibit large levels of slack in the form of self-employment (Breza, Kaur, and Shamdasani 2021). Essentially, workers turn to self-employment in the absence of work at the prevailing market wage. Labor is thus severely rationed in developing countries; in other words, if the worker was able to find work at the prevailing market wage, they would prefer that over self-employment. As a result, self-employment has been referred to as "disguised unemployment" or "forced entrepreneurship" in the literature.

In this paper, I exploit spatial variation in the exposure to roads following a large rural road building program in India to examine how individuals in the working-age population spend their time. Specifically, I investigate whether they spend more time in a day on wage employment as opposed to self employment. If increased spatial integration through rural roads brings more opportunities, workers will spend less time on self-employment and more time working at the market wage outside the household.[1]

Increased spatial connectivity promotes market integration and leads to a reallocation of workers out of agriculture (Asher and Novosad 2020). However, roads do not meaningfully contribute to the growth of village firms or predicted consumption, at least in the short to medium run. In a similar vein, Shamdasani (2021) finds that increased market access allows some households to transition out of agriculture, but this effect is concentrated among those within commuting distance to towns where non-agricultural jobs are available. Thus, despite infrastructure provision, access to urban centers remains severely limited.

Among agricultural households, roads increased the use of agricultural technologies and diversified their crop portfolio. The adoption of newer agricultural methods and the usage of High Yield Variety (HYV) seeds can also lower the amount of time spent working, freeing workers up to seek market work. Greater market integration also lowers prices (by lowering transport costs) and increases the availability of non-local goods (Aggarwal 2018). Additionally, roads pulled teenage workers out of school to join the labor force, but keep younger children in school longer. Consistent with a human capital model, Adukia, Asher, and Novosad (2020) find that children stay in school longer when nearby labor markets offer high returns to educational investment and least when it implies high opportunity costs of schooling.

I find that individuals in the working-age population are spending about 61 fewer

[1]It is worth noting that given the high levels of slack in the Indian rural labor markets, the intensive margin of time spent on market employment is arguably more important than the extensive margin. There will be a mass of workers whose principal activity is still self-employment; however, they may be able to find more hours of market work following road construction.

minutes in a normal day on employment and related activities. This decrease is offset by an increase in time spent in the production of good for own final use and time spent on self-care and maintenance. However, the mechanisms are unclear. I find that households in more exposed districts also have lower monthly total expenditure, but whether this is a price effect or a transition to self-sufficiency (an increase in production for own consumption) is unclear. Taken together with other findings in the literature, these results also suggest that roads alone are insufficient for economic transformation of villages and these remote areas may continue to lack economic opportunities.

2. Context & Data

The *Pradhan Mantri Gram Sadak Yojana* (PMGSY) – the Prime Minister's Village Road Program – was launched in 2000 by the Government of India. The main goal of the program was to establish reliable, all-weather connectivity to eligible villages by constructing all-weather roads. Such roads were to connected these unconnected villages to nearby villages already connected by an all-weather road, nearest all-weather road, the market center, or the block headquarters.

PMGSY is fully funded by the central government, but is managed by the state governments. Each state generates a list of all unconnected villages within the state, with villages ranked in descending order by population size, as recorded in the 2001 Population Census (Asher and Novosad 2020; Shamdasani 2021; PMGSY 2005, 2012). Highest priority is given to villages with a population of at least 1000, second highest priority to villages with a population size between 500 and 1000, and ultimately to villages between the size of 250 and 500. The consolidated priority ranking of villages across the state is also created after obtaining inputs based on district-level discussions and the District Rural Roads Plan (DRRP).

In order to be eligible for the program, a village had to be unconnected — located at least 500 meters away from an all-weather road or another village with such a road — and it should not already have a paved road. The program defined eligible villages using population cutoffs where population information was sourced from the Population Census of India (2001). Villages with a population of at least 1000 were given highest priority, followed by those with a population of 500, and then 250, and then all remaining villages. The program also included some road upgradation, but only in districts where all qualified villages had already received all-weather roads (PMGSY 2012). The program is still active as of the writing of this paper. By 2024-2025, the program connected 170,875 villages and built roads spanning 777,768 kilometers.

The main dataset is the Time Use Survey (2024) for India. It is a household level survey conducted by the National Sample Survey Organization (NSSO). For all members of a household above the age of six, the survey reports the time disposition along with the detailed activity code following the International Classification of Activities for Time Use Statistics (2016).

I use the mapping available via the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG, Version 2.0) created by Asher et al. (2021), which provides village-level identifiers (*shrids*) with consistent boundaries over time, to districts. Because some district boundaries changed during the last decade, I merge split districts back to their parent districts manually in order to consistent geographic units.

The SHRUG database also contains information on roads built under PMGSY in each village. Asher and Novosad (2020) web-scraped the PMGSY website and mapped details of road construction, such as completion date, sanction cost, sanction year, road length, etc., to the SHRUG database at the village level.

3. Empirical Strategy & Results

I aggregate data to the district level and create an average measure of minutes spent in various activities. I estimate the following cross-sectional regression specification:

$$Y_{ds} = \beta \times SharePopExposedToRoad_{ds} + \gamma_s + \epsilon_{ds} \tag{1}$$

where the outcome Y_{ds} is the average number of minutes spent in district d in state s performing a specified activity.[2] I exploit variation within state by including a state fixed effect, γ_s, and cluster my standard errors at the state level to allow for arbitrary correlations within state. β is the parameter of interest and is identified from variation between districts and within state stemming from the differential exposure of population to roads built by the program. I only retain households that reside in rural areas (because the program targeted villages) and I only look at normal days. My final dataset has information on 610 districts across 31 states. The lack of panel variation implies that my results are to be interpreted as mere correlations and not as a causal effect of increased connectivity.

Figure 1 shows the distribution of population exposed to roads under the program by early 2015. This is the "treatment" variable. The share of population exposed is higher in north Indian states, as seen in Dasgupta, Karandikar, and Raghav (2024), and is consistent with Asher and Novosad (2020), who mention that states in Southern India generally had superior infrastructure.

The results from estimating Equation 1 are reported in Figure 2 (and Table A1 in the Appendix). I restrict my attention to individuals in the working-age population (15-64). The estimate on employment suggests that a 1 percentage point increase in the share of population exposed to roads is associated with a 61 minute decline in time spent on

[2]In cases where multiple activities were performed within the same block, I assume that the time duration is split evenly for simplicity.

employment. This is mostly offset by a 48 minute increase in production of goods for own final use. There is a significant 30 minute increase in self-care and maintenance – another way in which the decreases are offset. The remaining estimates are statistically insignificant.

In Figure 3 (and Table A2 in the Appendix), I look at the status of an activity–whether it is paid or unpaid. The first estimate suggests a decline in paid labor by 72 minutes in districts with a greater share of the population exposed to roads. I split paid labor into 3 categories reported in the data: self-employment, wage employment, and casual employment. I find that the aforementioned decline in paid labor is entirely from regular salaried/wage employment outside the household.

4. Discussion & Conclusion

In more exposed districts, individuals are spending less time on paid labor and more time on unpaid labor, primarily in the production of goods for own final use. One possible explanation for this is that spatial integration increased wages enough for people to lower the hours of labor supplied (income effect). While I do not observe wages in the data, monthly total household expenditure is reported. I use it as a proxy to indirectly test this hypothesis. I find that a 1 percentage point increase in the share of population exposed to roads is associated with a decline in total monthly expenditure by INR 3400, which is about a 29% decline on the average expenditure of INR 11750.

Increased spatial integration lowers the prices of goods and increases the supply of non-local goods (Aggarwal 2018). Households can maintain the same level of consumption while spending less because prices are lower. In fact, a conservative calculation by Aggarwal (2018) finds that the price level fell 3% after villages were connected. Unfortunately, prices are not observed in the data. The availability of cheaper goods might also induce households to shift towards purchasing cheaper inputs and intermediate goods and produce things for own consumption–a move towards self-sufficiency. Indeed, the decrease in wage employment being offset by an increase in consumption suggests that this may be happening.

Seasonality is important factor in India, largely due to the agrarian sector. Much work in rural labor markets is seasonal, and so it is possible for there to be a seasonality in wage employment outside the household. For instance, households might increase hired labor use during the harvesting or sowing season. In the future, I want to look at the possibly heterogeneous effects during peak and lean months.

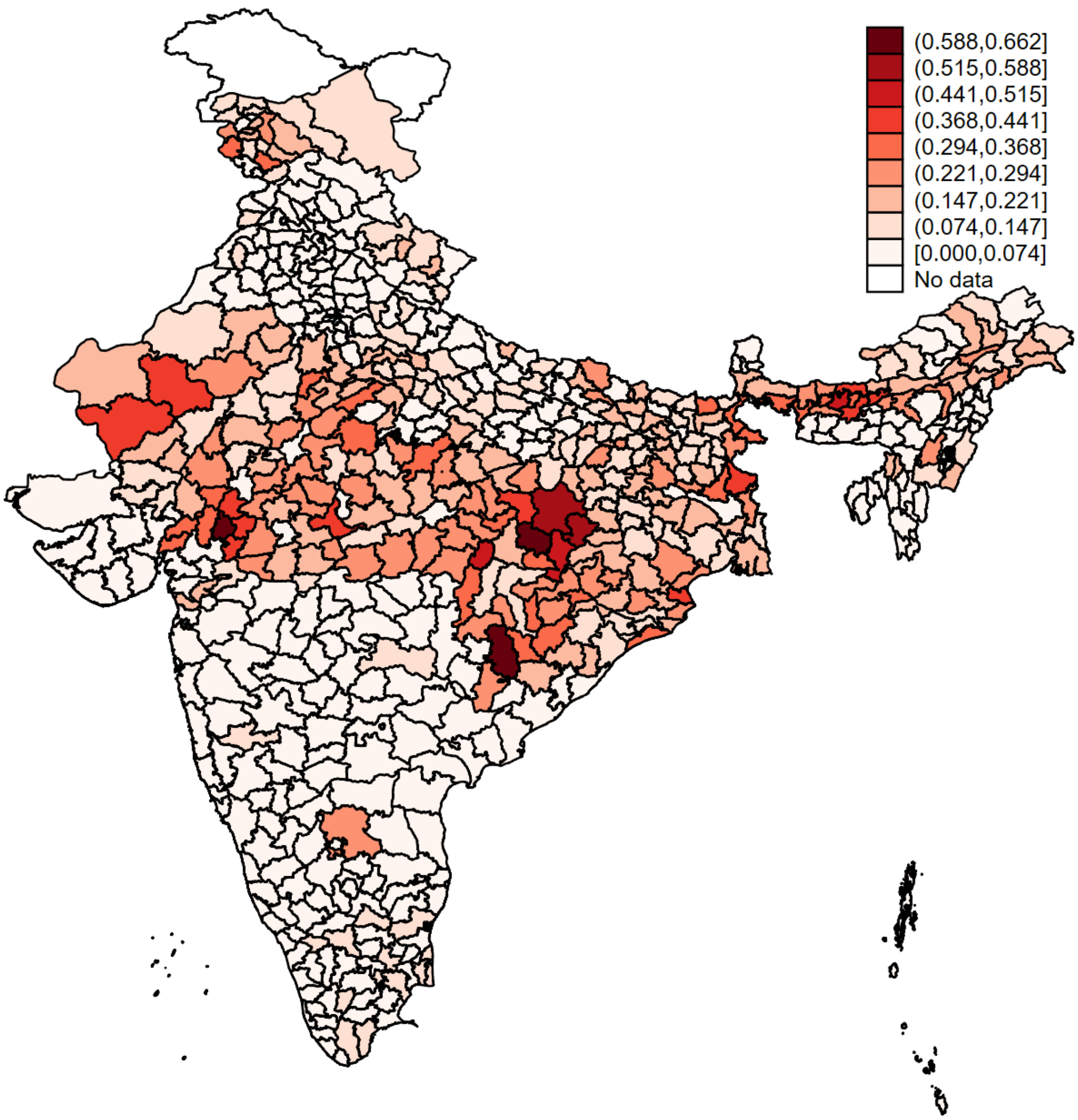

FIGURE 1. Distribution of completed new roads under the program by early 2015

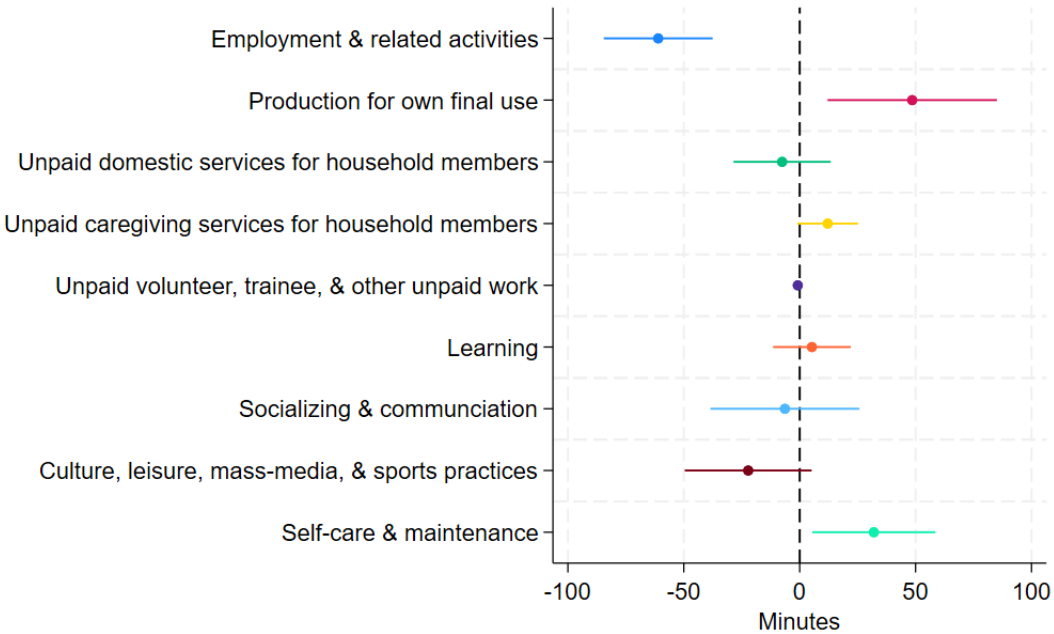

FIGURE 2. Time use of working-age population

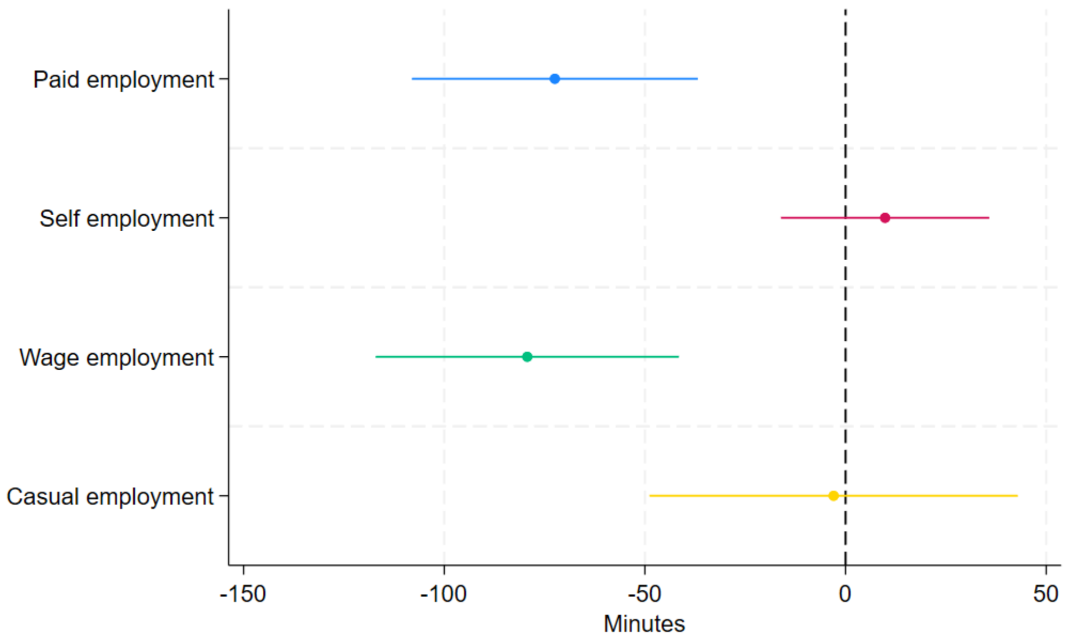

FIGURE 3. Time use by types of paid employment

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Employment	Production	Unpaid domestic	Unpaid caregiving	Unpaid volunteer	Learning	Socializing	Culture	Self-care
Share exposed	-61.039***	48.538**	-7.572	12.093	-0.830	5.280	-6.363	-22.202	32.005**
	(13.835)	(21.523)	(12.356)	(7.719)	(0.756)	(9.869)	(18.930)	(16.125)	(15.653)
Constant	232.543***	31.288***	159.577***	37.825***	0.877***	42.137***	119.929***	132.332***	683.491***
	(1.543)	(2.401)	(1.378)	(0.861)	(0.084)	(1.101)	(2.112)	(1.799)	(1.746)
Observations	610	610	610	610	610	610	610	610	610
R-squared	0.480	0.538	0.455	0.382	0.172	0.244	0.227	0.319	0.186

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE A1. Time use of working-age population

VARIABLES	(1) Paid labor	(2) Self-employment	(3) Wage employment	(4) Casual employment
Share exposed	-72.438***	9.848	-79.311***	-2.975
	(20.989)	(15.295)	(22.263)	(27.038)
Constant	343.337***	161.036***	77.229***	105.072***
	(2.342)	(1.706)	(2.484)	(3.016)
Observations	610	610	610	610
R-squared	0.400	0.349	0.436	0.325

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE A2. Time use by types of paid employment