Road Access, Fertility and Child Health in Rural India

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Abstract

Expansion in access to public infrastructure can have varied, micro-level impacts. In this paper, we use quasi-random access to rural paved roads through a large-scale road-construction program in India to study how road access impacts fertility decisions and investments in child health. We find that increased access to paved roads at the district-level leads to a rise in fertility, improved investments in children–measured through breastfeeding duration and immunization—and lower infant mortality. We also investigate the potential labor market mechanisms that drive these effects, and heterogeneity in the impacts by plausibly exogenous variation in levels of female labor force participation (FLFP). We find that in districts with lower levels of FLFP, the effects on fertility and child health are driven by paved road access causing women to substitute away from paid employment into full-time domestic work. On the other hand, in districts with higher levels of FLFP, the effects are likely driven by roads leading to increased access to healthcare infrastructure.

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JEL Classification: I12, I15, O12, O15, O18, R23

1 Introduction and Background

Rural infrastructure projects can determine key micro-level household decisions and outcomes such as employment (Dinkelman 2011), uptake of institutional healthcare (Aggarwal 2021), schooling (Khandker & Koolwal 2011) and poverty (Khandker et al. 2009; Duflo & Pande 2007). The 'Pradhan Mantri Gram Sadak Yojana' (henceforth PMGSY) is a large-scale public road construction program, launched in December 2000, that mandated the construction of all-weather roads connecting habitations within Indian villages with a population of at least 500 to the nearest market center.[1] We study the impact of the quasi-random access to paved roads on fertility, child health and women's employment. Other studies show that the PMGSY affected rural labor markets (Asher & Novosad 2020; Aggarwal 2018), diversified crop portfolios and agricultural outputs (Shamdasani 2021) and improved educational attainment (Adukia et al. 2020). Greater connectivity via paved roads also increased access to formal healthcare facilities, likelihood of institutional births and improved health inputs for both mothers and children (Aggarwal 2021). We provide the first evidence that this access to paved roads also influenced fertility, alongside health inputs in children. In doing so, we add to the relatively sparse literature on the supply-side constraints to child healthcare.

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[1]As of 2022, it has provided connectivity to over 90 percent of the 178,000 eligible habitations by building more than 780,000 kilometres of roads at a cost of $48 billion during its lifetime. See the World Bank brochure (2022) for more details.

In general, large scale public infrastructure programs such as road construction, stand to shape household-level decisions on child health investment and fertility through both demand and supply-side channels. They have an income effect – by reducing poverty and changing the economic ability to invest in children (Khandker et al. 2013, 2009; Gibson & Rozelle 2003; Lenz et al. 2017; Parikh et al. 2015; Saing 2018; Medeiros et al. 2021; Aggarwal 2018) and a substitution effect – manifesting through changes in employment opportunities and wages that affect the time allocation problem posed to adults in the household, and in particular, women (Dinkelman 2011; Lei et al. 2019; Sedai et al. 2021; Hjort & Poulsen 2019).[2] Simultaneously, they influence the supply-side dimension of healthcare by reducing transportation barriers and enabling access to extant—but not always reachable—facilities (Aggarwal 2021). We demonstrate how both the demand-side and supply-side determinants of fertility and child healthcare respond to these 'big-ticket' interventions, which can have both intended and unintended general equilibrium effects.

We draw upon a rich literature on the response of child health investments and fertility to erstwhile shocks that are akin to the demand-side effects of infrastructure. Cannonical models in this arena highlight how fertility is affected by the time allocation problem posed to women (Becker et al. 1960; Schultz 1969) and the investments made in children that determine their 'quality' (Becker & Lewis 1973). Similarly, there is a large, albeit mixed, literature on the implications of income shocks on fertility and child health. [3] Adsera and Menendez (2011) find evidence that fertility is pro-cyclical using data on 18 countries in Latin America, meaning that fertility declines during economic downturns. J. Kim and Prskawetz (2010) show that unemployment is linked to higher fertility in Indonesia. Anukriti and Kumler (2019) find that in India, impacts of tariff cuts imposed by trade reforms differ by women's 'status' (income group, caste and education level). 'Low status' women experience increased employment, and simultaneously have higher fertility and lower child mortality (especially for female children) under tariff cuts, while the opposite is true in the case of 'high status' women. Ferreira and Schady (2009), review the existing literature and identify that in low income countries in Asia, Africa and middle-income countries in Latin America, infant mortality and child health is pro-cyclical. Baird et al. (2011), use individual level data on infant mortality from 59 countries to confirm that economic downturns lead to higher infant mortality. They also show that female children's outcomes are more sensitive to these shocks.[4]

Furthermore, the literature on the direct impacts of public infrastructure on employment opportunities reveals a broad consensus that this impact tends to be positive, with evidence of higher gains in female employment. Dinkelman (2011) finds that rural electrification raises female employment in South Africa. Lei et al. (2019) use household survey data to show that access to roads and frequent bus transport raises male and female non-agricultural employment in India – with larger effects on women. Sedai et al. (2021) show that reliable electrification increases employment in India – with larger effects on women's employment – and improves women's say in purchase and fertility decisions. Hjort and Poulsen (2019) use data from 12 countries

[2]See Calderón and Servén (2014) for a summary of existing literature.

[3]Several papers note that the fertility response to economic fluctuations is pro-cyclical in currently rich countries (Sobotka et al. 2011; Currie & Schwandt 2014) – meaning that fertility declines with recessions (most commonly measured by increased unemployment in these contexts). Related literature documents that infant mortality and child health can be counter-cyclical. Children conceived during periods of high unemployment in the United States have reduced rates of infant mortality and very low or low birth weight (Dehejia & Lleras-Muney 2004).

[4]Evidence on pro-cyclicality in infant mortality and child health is presented in Bhalotra (2010) for India, Cutler et al. (2002) for Mexico, and Paxson and Schady (2005) for Peru. Miller and Urdinola (2010) find evidence for counter-cyclicality in infant mortality during income shocks in coffee-growing Colombia.

in Africa to show that access to high-speed internet raises employment rates. Jensen and Oster (2009) find that access to cable TV influences gender attitudes among women in India, reduces reported acceptability of domestic violence by men, increases reported mobility and participation in household decision making and reduces fertility.

Given the role mother's employment plays in determining investments in children and fertility, we could expect that the effects of public infrastructure might vary by the norms around female labor force participation (FLFP). In order to investigate possible heterogeneities in these effects due to differences in the norms around FLFP, we also look separately at child health investment and fertility effects of road construction for subsamples of districts with high versus low levels of FLFP. We identify these subsamples by using exogenous, geographical variation in soil texture that drives the extent of FLFP in agricultural processes. The 'loamy' versus 'clayey'-ness of soil influences the extent to which deep tillage of soil is possible, which in turn affects the extent to which female labor is involved in the cultivation process. The loaminess of the soil determines the machine usage in land tilling. These machines are typically operated by men, and machine tilling further reduces the demand for downstream tasks such as weeding – an operation in which female specialization is more common (Afridi et al. 2020). Thus, higher levels of 'loaminess' is associated with lower FLFP (Carranza 2014).

Our analysis reveals that road access causes a simultaneous improvement in the quality of child-rearing (by increasing breastfeeding duration and child immunization rates and reducing infant mortality) and fertility (measured by the number of children born to women in the year of road construction). We show that while the impact of paved road access on the quantity and quality of children is the same in districts with relatively lower and higher levels of FLFP ('high' and 'low' loam districts), the mechanisms that drive these effects might differ. In districts with relatively lower levels of FLFP ('high' loam districts) the improvements in the quality of child rearing and increase in fertility appear to be driven by road access causing the substitution of womens' time away from paid employment into full-time domestic work. On the other hand, in districts with relatively higher levels of FLFP ('low' loam districts), we do not find evidence that female time allocation changes in response to increased road access. However, we find suggestive evidence of an increase in medical expenditure in these districts, which could drive the effects on child quality and fertility. As we are unable to observe supply-side changes to healthcare provision, or changes in household income in the data, we cannot comment on how these could drive the effects we find.

Our study makes several contributions. First, we bring together the growing literature on how economic shifts influence fertility and child health in developing contexts and the literature on the health and family impacts of public infrastructure. Second, we extend the scope of outcomes previously studied in the literature, and to the best of our knowledge provide the first causal evidence of the impact that increased access to paved roads can have on fertility. We investigate a large set of related health outcomes, that include breastfeeding duration, immunization and infant mortality. In doing so, we show how increased access to paved road causes improvements in the 'quality' of children while simultaneously influencing the 'quantity' of children households choose to have. Lastly, we synthesize data from various sources and draw on rich household surveys to study outcomes and possible mechanisms. We combine data from the National Family and Health Survey (NFHS) and the Employment and Unemployment Surveys conducted by the National Sample Survey Organisation (NSSO) with information on road construction in the Socioeconomic High-resolution Rural-

Urban Geographic Platform for India (SHRUG). This allows us to use quasi-random variation in access to paved roads at the district level to study the effects of road access on a large set of maternal and child outcomes, including health, expenditure and employment. We also study heterogeneity by the extant norms around female labor force participation (FLFP), by combining the roads and health data with soil data from the Soils of India (2001) dataset. We use exogenous variation in the extent of deep-tillage possible[5] at the district level, that influences the extent of female involvement in the agricultural labor force to study how the impact of road access might vary between households in 'high' versus 'low' loam districts.

This paper is structured as follows. Section 2 explains the data sources and variable construction. Section 3 lays out the empirical strategy. Section 4 presents the main results. Section 5 discusses possible mechanisms. Section 6 concludes.

2 Data

2.1 Road Construction

We obtain data on road construction from the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG), which is a collection of datasets that encompass economic, demographic and electoral indicators at the village and town-level[6]. To measure baseline access to paved roads, we source data from the Village Directory of the 2001 Population Census, which records the type of road in each village. Data on the provisioning and construction of roads under PMGSY, over the period 2002-2017, is contained therein and sourced from the Online Management and Monitoring System (OMMS) for the program. A village *receives* a PMGSY road in year y if it did not have access to paved roads at the baseline, and construction was completed sometime within year y.

We aggregate the roads data to the district level, since that is the smallest geographical identifier that is available for all other datasets used in our analysis. The aggregation procedure follows a strategy much like Aggarwal (2018). For each district in any given year, we compute the cumulative share of the district's rural population—using data from the 2001 Population Census—that had received a new road under PMGSY until that year. Simply, we sum the population of all villages in the district that received a PMGSY road and divide this sum by the total rural population of the district. By construction, the outcome of this exercise, denoted as *Road Growth*, is increasing over time and bounded in the interval [0, 1].

2.2 Soil Texture

We gathered data on soil composition from Soils of India (2001), created and disseminated by the National Bureau of Soil Survey and Land Use Planning.[7] Their spatial data on soil surface texture, physiography and depth, among others, was mapped to Indian districts using the administrative boundaries as of the 2001 Population Census. We are able to do this matching for 564 out of the 584 districts at the time. Akin to prior work in this area (Carranza 2014; Afridi et al. 2020), we construct a measure of the depth of soil tillage by using data

[5] We compare the share of loamy soil to the share of clayey soil at the district level, to classify districts as 'high' versus 'low' loam. Details on the construction of this variable and its use in the analysis are provided in Section 2

[6] The data can be obtained at: https://www.devdatalab.org/shrug

[7] We obtain the data from the replication dataset provided by Carranza (2014). We thank Abhiroop Mukhopadhyay for providing access to the district mapping (2001 Census) in this data.

on soil surface texture. In particular, soils with a larger share of loam content and correspondingly smaller share of clay content have deeper tillage. Therefore, like Afridi et al. (2020) we subtract for each district the fraction of clay content in its soil from the fraction of loam content. We then compute the median of this difference across all districts, and assign each district into one of two groups—*High Loam* or *Low Loam*—based on a comparison of their difference with the median. High Loam districts are those for whom the difference exceeds the median, and Low Loam districts are those for whom the difference is at most the median.

2.3 Healthcare and Health Outcomes

We use the National Family and Health Survey (NFHS) for child healthcare and health outcome data. The NFHS is a nationally representative survey administered by the Ministry of Health and Family Welfare (MoHFW) and the Indian Institute of Population Sciences (IIPS). We utilise three of the four rounds for which data are available: NFHS-1 (1992-93), NFHS-2 (1998-99) and NFHS-4 (2015-16). NFHS-3 could not be used because it lacks district identifiers. Our primary focus is on NFHS-4, which covers over 500,000 households across the country and is also representative at the district-level, unlike the previous three rounds. The dataset contains questions on subjects such as fertility, mortality, family planning, immunization, nutrition, and maternal and child health. A distinguishing feature of the NFHS, vis-a-vis other large-scale health surveys in India, is that information on mortality, breastfeeding and immunization is available for all children aged 0-5 years in the household.[8] Our outcomes of interest are fertility, breastfeeding, child immunization and infant mortality.

To compute *Fertility*, we use retrospective birth history in the woman-level recode of NFHS-4, we create a psuedo-panel wherein each observation corresponds to one year in the life of a woman. We only consider years where the woman was aged between 16 and 41[9], and we limit the timespan to post-PMGSY years, i.e. from 2002 until 2016. Then, for each woman-year combination, fertility is defined as a binary outcome that equals 1 if the woman gave birth in that year, and 0 otherwise. The remaining outcome variables are constructed from the child-level recode of NFHS-4. *Breastfeeding Duration* is pre-computed within the NFHS data for all living children and records the number of months that the child has been breastfed. For immunization, we construct a *Vaccine Index* by using questions on the child's uptake of vaccines and supplements, such as Polio, BCG, Diptheria, Tetanus and Vitamin-A. Each of these responses is a binary variable that indicates whether the child had received that vaccine or supplement. Using the Generalised Least Squares approach to dimensionality reduction outlined by M. L. Anderson (2008), we build a summary index for immunization.[10] Lastly, we define *Infant Mortality* as a binary outcome that equals 1 if the child died within twelve months of their birth, and 0 if they lived past the first year of birth. It is coded as missing for children who are under the age of twelve months at the time of interview.

[8] Other datasets, such as the DLHS and IHDS, contain this data only for the most recent and two most recent births, respectively.

[9] The NFHS collects data for women aged 16-49, but we restrict it to 16-41 in order to maximise comparability between our main sample and the placebo test (see Section 4.1). Our results are robust to the inclusion of women aged 42-49 in the sample.

[10] This procedure can be thought-of as inverse-covariance weighting, wherein a variable receives a lower weight if it strongly covaries with other variables used to build the index. Essentially, every component variable receives a weight commensurate with their informational content.

2.4 Other Data

To identify and understand the mechanisms behind the results on health investments and outcomes, we use the Employment and Unemployment Surveys conducted by the National Sample Survey Organisation (NSSO). We limit analysis to *thick* rounds of the survey that administered questions on labour market outcomes and household consumption to over 120,000 households.[11] The data come from rounds 61 (2004-05), 64 (2007-08), 66 (2009-10) and 68 (2011-12) of the NSS and is representative at the district level.

Employment outcomes are available for all individuals within the sample, but we evaluate them only for adults who were both willing and able to work. An individual is deemed willing and able to work if they meet all of the following criteria: (i) were not full-time students (ii) were not pensioners, rentiers or remittance-receivers (iii) were not unable to work due to disability (iv) were not engaged in begging or prostitution. Since both the job classification and industry were available for employed individuals, we use these to construct second-order binary measures of employment such as work in agriculture or engagement in unpaid household work.

Household consumption expenditure is recorded separately for various types of goods. Data on different expenditure categories, such as food, healthcare and consumer durables, is collected for either a 30-day or 365-day recall period. The categories for each time period are mutually-exclusive, i.e. data for any given category is available for either the preceding month or preceding year, but not both. Since the survey recorded nominal expenditures, we deflate the figures using the consumer price index (CPI), for which the base year of choice was 2010. Our interest lies in two outcomes: (i) annual household expenditure (ii) the fraction of annual household expenditure that was spent on medical items.

2.5 Sample Characteristics

The main sample uses the birth recode of the NFHS and contains approximately 200,000 child births between 2010-16 across 621 out of 640 Indian districts.[12] Fertility data is derived from the woman recode, which records data for 300,000 women in the same spatial and temporal frame. Data on household expenditure, employment patterns and prevalence of agricultural work is available for 618 of those districts. Table 1 presents the summary statistics on all of these outcomes, alongside relevant covariates.

The last column of table 1 reveals that *High Loam* districts had higher levels of fertility and infant mortality, although no difference emerges in health investments – breastfeeding and vaccination, alike. In terms of differences in womens' outcomes, the results are somewhat mixed. Notably, *Low Loam* districts contain fewer woman-headed households and the uptake of secondary education is lower among the women in these districts. On the other hand, women in *Low Loam* districts are more likely to be employed with pay in either salaried work or wage labour outside of the household enterprise. Correspondingly, they are also less likely to be engaged solely in domestic work. This suggests that the higher female labour force participation in *Low Loam* districts stems from employment in agriculture and allied areas, as shown by Carranza (2014). Hence, we argue that *Low Loam* districts exhibit norms that are more favourable towards women's employment but

[11] *Thick* survey rounds were quinquennial, while *thin* rounds were conducted during the interim between two thick rounds. The sample size for a thin round was anywhere between 40,000 and 50,000 households.

[12] NFHS-4 used the administrative boundaries from the 2011 Population Census. As of 2022, India has 737 districts.

not necessarily more gender-equal.[13] However, previous work by S. Anderson and Eswaran (2009) reveals that that women's bargaining power and control over household resources is tied to employment outside of family farms, i.e. paid work. Further, since we find that paid employment among women is more common in *Low Loam* districts, we can also expect that the average woman in these districts has higher bargaining power than her counterpart in *High Loam* districts.

We also note that while at baseline road access does not significantly differ between *High Loam* and *Low Loam* districts, the intensity of PMGSY road construction is marginally higher among the latter. However, a visual inspection of Panel A in Figure 1 suggests road construction and soil texture do not strongly covary. If anything, *High Loam* districts are usually found clustered together in the northern and central states, alongside coastal regions in southern India. On the other hand, much of the road growth occurred in central regions of India — in states like Rajasthan, Madhya Pradesh, Bihar, Odisha and West Bengal. This is presented more extensively in Panel B of Figure 1, which illustrates the variation in road access at baseline and the intensity of road construction. Panel A shows that at the baseline road access follows a mostly symmetric distribution, with 369 of 618 districts being such that over half of their rural population received access to paved roads. The coverage of road construction under PMGSY seems to follow a Pareto-like distribution, as evident in panel B. In fact, within most districts less than 20 percent of rural residents received a road under the program. Nonetheless, there is variation in program intensity across both space and time that enables our analysis. Figure (2) presents binscatter plots of healthcare, employment and expenditure outcomes against quantiles of *Road Growth* before the main analysis in subsequent sections. The relationship between *Road Growth* and these outcomes appears to be non-linear and non-monotonic, although not enough can be inferred about the structure of this relationship due to the loose confidence bands.

3 Empirical Strategy

We use quasi-random improvements in access to paved roads at the district level to study how they affect households' fertility decisions, investment in child health and, by extension, the effects on infant mortality. Owing to the lack of village indicators in the NFHS data, all measures of road access are aggregated to the district-level for each program year up until 2016. The resultant measure is a (weakly) increasing function of time and hence, allows us to exploit both intra-district and inter-district variation. Our interest lies not just in studying the unconditional effect of roads on the aforementioned outcomes, but also in how differences in norms around FLFP mediate this effect.

To proxy for gender norms we leverage information on local soil texture to classify districts into either *High Loam* or *Low Loam*. This follows from the fact that districts with higher loam and lower clay content exhibit greater female labour force participation, primarily within the agricultural sector (Carranza 2014; Afridi et al. 2020). Our procedure for this classification is as indicated in section 2.2. It bears mentioning that the results are robust to changes in the soil classification scheme, such as using the median level of loam content—as opposed to the difference between loam and clay content—as the criteria to categorise districts as *Low Loam* and *High Loam*.

[13] Women in *Low Loam* districts enjoy higher labour force participation due to agricultural employment, but this advantage does not extend to measures of household decision-making or educational attainment that are captured in the NFHS data.

3.1 Fertility

The estimating equation is given below, and is run separately for *High Loam* and *Low Loam* districts:

$$Y_{whdt} = \beta_0 + \beta_1 Roads_{dt} + \gamma X_{wht} + \delta_d + t + (\delta_d \times t) + \epsilon_{whdt} \tag{1}$$

where each observation is an woman w in household h living in district d and born in year t. X_{wht} is a vector of individual and household-level covariates including the woman's age in year t, her age during her first childbirth, indicator variables for the household's religion and social group, household size, the household's wealth index ranking and ownership of agricultural land.

The key coefficient is β_1, which represents the marginal effect on Y of a percentage point increase in road access among rural residents of district *d* due to PMGSY. We expect β_1 to be downward-biased, and this an unavoidable artefact of aggregating the roads data to the district-level. Consider household h in the sample, residing in village v of some district d. It is entirely possible that none of the improvements to road connectivity within that district stem are local to village v, i.e. other villages receive all the PMGSY roads. In such cases, β_1 captures only indirect effects of road construction on household h, enabled by (possibly) new access to non-hyperlocal markets in nearby villages or cities.

We cannot rule out contemporaneous changes to both demand and supply-side determinants of healthcare, such as interventions by district administrations and the availability of (new) local health centres, medical personnel and community health workers. To account for them, we include both district fixed effects (δ_d) and district-specific linear time trends ($\delta_d \times t$) in the estimating equation. The coarseness of these fixed effects may be a cause of concern, since there may be heterogeneity at the village-level that remains unaddressed.[14] One recourse for this limitation is including fixed effects at the level of each primary sampling unit (PSU) into equation (1), because each PSU in the NFHS sampling scheme corresponds to exactly one (unidentifiable) village. Our results on both fertility and child healthcare are robust to this change in specification and are presented in Tables 7 and 8 in the appendix.

3.2 Child Healthcare

We employ the following variation of equation (1), evaluated on a sample of children aged 0-5 years and born during 2010-2016:

$$Y_{ihdt} = \beta_0 + \beta_1 Roads_{dt} + \gamma X_{iht} + \delta_d + t + (\delta_d \times t) + m + \epsilon_{ihdt} \tag{2}$$

where each observation is some child i from household h living in district d and born in year t. The dataset is a psuedo-panel, since we use household covariates (X_{iht}) that are observed only during the interview year, but are treated as time-invariant over the reference years. All regressors retain their definitions from equation (1), with the only exception being the inclusion of the child's age and gender as additional controls within X_{iht}, alongside with fixed effects for the child's month of birth (m). Similarly, δ_d denotes district fixed-effects and $(\delta_d \times t)$ denotes the district-specific time trends. The interpretation of β_1 and associated caveats from

[14]Though some information on healthcare supply is available in the village directory of the 2011 Population Census, it cannot be mapped to the NFHS data because the latter lacks village identifiers. Interested researchers may want to look at recent work that employs machine learning to predict village-level healthcare supply using subsets of this data (R. Kim et al. 2021).

equation (1) also carry over.

4 Results

This section presents the results from specification (1) on female fertility and child healthcare. Based on our priors about the differences in female labor force participation across regions with different soil textures, we would expect to see lower rates of fertility and higher investments into child healthcare within *Low Loam* districts.

4.1 Fertility

Panel A of Table 2 reveals how fertility responds to road construction. From column (1), we see that better local road connectivity lead to an increase in fertility, when evaluated over all available years, i.e. 2002 to 2016. The interpretation is straightforward – in a given year, each percentage point of growth in road access increases the chances of a woman having a birth in that year by 0.12 percentage points. Therefore, in a random sample of 100 women, this translates into 12 additional births. Though columns (2) and (3) suggest that this increase in fertility is relatively lower in *Low Loam* districts, using a Chow Test for Structural Stability we are unable to reject the hypothesis that the two effect sizes are equal.

In columns (4) and (5) we undertake the same analysis on a truncated timespan covering years from 2010 to 2016. Our motivation for this is twofold. Firstly, fertility often responds to economic fluctuations with a lag (Sobotka et al. 2011). Therefore, if rural roads affect fertility through employment or income channels, then a delayed evaluation seems reasonable.[15] At the start of this time interval the program would have been in-effect for over nine years. This should provide households the requisite time to factor these road improvements into their own decision-making and hence, enable us to study the long-term effects of roads on fertility. Incidentally, that also distinguishes our analysis from that of Aggarwal (2021), who finds no tangible change in fertility over the immediate term.[16] Secondly, we have data on both infant mortality and vaccination for children born between 2010-2016. Consequently, evaluating the fertility response during this period is informative about the 'quality-quantity trade-off' faced by households in family planning decisions. For instance, Kalemli-Ozcan (2003) argues that lower infant mortality rates reduce the uncertainty surrounding the number of surviving children, which can reduce household demand for more children under convex preferences. Empirical analyses have also alluded to a relationship between infant mortality and fertility. Anukriti et al. (2022) show that reductions in postnatal infant mortality—arising due to households engaging in sex-selective abortions—led to reductions in overall fertility.[17] Further, evidence from malaria eradication programs shows that a decrease in the incidence of disease leads to both lower infant mortality and higher fertility (Bhattacharjee & Dasgupta 2019; Apouey et al. 2018). More pertinently, assessing how a policy affects both infant mortality and fertility is key to understanding its implications on demographic transition Nandi, Summan, et al. (2022).

[15] While we continue to use contemporaneous road growth as the regressor here, a large fraction of the roads built under PMGSY had been delivered by 2010. Adukia et al. (2020) provide a time-disaggregated view of road construction under the program in Figure 1 - Panel A of their paper.

[16] Her analysis uses retrospective fertility data from DLHS-2 and DLHS-3 that covers post-PMGSY years from 2001 till 2008.

[17] However, consensus on the prevalence of the quality-quantity trade-off remains absent, with Schultz (2007) suggesting that it is mostly localised among high-income urban societies, i.e. not the beneficiaries of rural roads.

We observe a much stronger fertility response in the truncated sample, with the marginal effect of road growth stood at 1.7 percentage points in *Low Loam* and 1.4 percentage points in *High Loam* districts. However, we are once again unable to reject the hypothesis of identical effect sizes. More pertinently, the fertility response in 2010-16 is up to ten times as strong as that in 2002-16, which suggests that fertility does respond to rural roads with a lag. Hence, if infant mortality reduces contemporaneously, then as an unintended consequence rural roads may actually hinder the rate of demographic transition. In such contexts, the positive implications for economic growth, borne out of increased human capital formation and labour force participation (Bloom et al. 2018, 2019), may be delayed. This is unlike some prior infrastructure interventions, such as the rural electrification program in the Philippines, wherein a decrease in fertility and higher labour force participation was observed (Herrin 1979).

An obvious concern here is the existence of pre-trends in fertility, which threatens the parallel trends assumption in our difference-in-difference analysis. To address this, we adopt the placebo test used by Aggarwal (2021). For the placebo sample, we use fertility data from 1998-2000. These are the pre-PMGSY years that retain most of the size and variation of our main sample.[18] Since pre-PMGSY years lack data on road construction, we map each year y in this time interval to its corollary y' in the period from 2014 to 2016. Then, the level of road growth in year y' is assigned to year y. For example, the level of road growth in district d during 1998 equals the level in 2014. Finally, we test the same specification as before, albeit on this placebo sample. Columns (6) and (7) present the results and demonstrate that there is no evidence of pre-trends in female fertility. Lastly, Panel B replicates the analyses in Panel A, but this time on a sample consisting all women surveyed in NFHS-4, i.e. of ages 16-49. Our results remain broadly unchanged, with only a small drop in average treatment effect arising after the inclusion of older women.

As an aside, based on the work by Anukriti and Kumler (2019) we look for subgroup heterogeneity in the fertility response across three margins: (i) education (ii) social category and (iii) household wealth and present the results in Table 9 (see Appendix). In columns (1) and (2) we find that the fertility increase is larger among women with more years of education. For context, fertility within the base group—women with no formal education—rises by 0.075 percentage points, while the effect among women with only primary education is 0.2 percentage points. From columns (3) and (4) we note that women in SC/ST households were up to 0.029 percentage points—30 percent of the average treatment effect—more likely to have children post-road construction when compared to women in non-SC/ST households. This bears mentioning because these groups have fewer children in the absence of PMGSY roads.[19] We posit that this may be due to *sanskritization*, whereby lower caste households emulate the behaviour of higher case households, that Kingdon and Unni (2001) have previously found within urban India. In columns (5) and (6) we see that wealthier households exhibited a stronger fertility response, with this "wealth differential" in the effect of roads being almost three times stronger in *High Loam* districts. Generally, however, we find little difference in these subgroup-specific effects between *Low Loam* and *High Loam* districts. Investigating such fertility dynamics further may be of interest for future work.

[18]For reference, women in the main fertility sample were aged between 16-41, while this range shrunk to 16-35 in the placebo sample (16-33 for 1998). Since the age range is strictly increasing over time (until 2005), going back further in time would have reduced it even more and made the two samples less comparable.

[19]For reference, the coefficient on the *SC/ST* dummy is both negative and significant.

4.2 Child Healthcare

We now turn to the healthcare investments made by households into their young children, for which we use equation (2). We present the relevant results in Panel A of Table (3).

Inspecting columns (1) and (2), we note that road growth leads to more months of breastfeeding among children aged 0-5 years. Once again, the effect is stronger in *Low Loam* districts, with the additional 2 months of breastfeeding amount to 13 percent of the mean. This is larger both relatively and absolutely than the 1.4 month increase we observe in *High Loam* districts. We recognize that this rise in breastfeeding may not necessarily arise due to a stronger household preference for child healthcare. In fact, Jayachandran and Kuziemko (2011) show that women in India choose to breastfeed due to its contraceptive properties, which is demonstrated by the rise in breastfeeding higher up the birth order. We test for this by including the child's birth order, alongside its interaction with road growth, as additional covariates in equation (2) and present the results in Table 6 (see appendix). Simply, we find no evidence of the rise in breastfeeding being fuelled by fertility-related reasons, with the interaction term being insignificant within *Low Loam* and weakly negative within *High Loam* districts.

The result on immunization is captured in columns (3) and (4). Akin to Aggarwal (2021), on the whole we find that vaccination outcomes are boosted by better road connectivity. Moreover, the heterogeneity induced by soil texture remains consistent; children in *Low Loam* districts benefit slightly more than their counterparts in *High Loam* districts. The increase of 1.7 index points within *Low Loam* districts constitutes a 16 percent improvement over the mean, while the corresponding 1.3 index point rise in *High Loam* districts represents 13 percent of the mean.

Knowing that improved access to roads is linked to higher healthcare investments, we should also expect better health outcomes among the recipients of these roads. We adopt infant mortality as the outcome for this exercise since both breastfeeding (Jayachandran & Kuziemko 2011) and vaccination against infectious diseases (Aggarwal 2021) help build immunity and mitigate the risk of infant mortality. Based on columns (5) and (6), we can affirm that the infant mortality rate does decline amid improved availability of all-weather roads. In *Low Loam* districts, each percentage point of road growth reduces the infant mortality rate by 2.2 percentage points. This translates into a 42 percent reduction over the mean, and suggests that better road connectivity could, in theory, drive down infant mortality rates to nearly-zero by itself. A similar albeit weaker effect is observed in *High Loam* districts, where the reduction in infant mortality amounts to 0.8 percentage points, or equivalently, 13 percent of the mean level.

Having established the results, we now check for pre-trends by utilising a similar strategy as in the case of female fertility. The sample for this placebo test consists of child-level data from NFHS-1 and NFHS-2 that together cover the years 1988-2000. Each year in this period is mapped to its corollary in 2004-2016, which is used to assign the level of PMGSY-induced road growth to the observation. The results of the placebo test are presented in Panel B of Table 3. We find no pre-trends in the measures of child healthcare, as can be verified from columns (1) through (6). We repeat this exercise two more times – once with only NFHS-1 and then with only NFHS-2, but the outcome remains unchanged. Therefore, we are able to rule out the possibility that the lack of pre-trends is an artefact of sample choice.

5 Mechanisms

We now turn to mechanisms that could explain the observed increase in both fertility and child healthcare investments. For instance, better road connectivity could improve market linkages and create economic opportunities for nearby residents. This job creation could bring about a pro-cyclical response in fertility and a contemporaneous income effect may encourage households to spend more on child health. But if women gain employment due to roads, then it reduces their available time for childcare and this substitution effect would manifest as reduced investments in child health. Another explanation is that rural roads facilitate easier access to both local and non-local healthcare facilities, especially during he monsoon season, when travelling on mud roads can become very difficult (Aggarwal 2021). This could boost uptake of institutional care, which can include vaccination of young children. We separately evaluate the merit of both explanations.

5.1 Employment

In Panel A of Table 4 we show how employment outcomes vary in response to road construction. For this, we use a specification that is a variation of equation (2):

$$Y_{ihdt} = \beta_0 + \beta_1 Roads_{dt} + \beta_2 Female_i + \beta_3 (Roads_{dt} \times Female_i) + \gamma X_{iht} + \delta_d + t + (\delta_d \times t) + m + \epsilon_{ihdt} \quad (3)$$

with each observation representing an individual i, aged between 16-60 years, belonging to household h in district d and interviewed in year t. The control vector X_{iht} comprises of indicators for the respondent's age, marital status, education, religion, social category, household's land ownership and the household's primary occupation. m denotes fixed effects for the interview month, which are included because the predominance of agriculture leads to seasonality in employment and expenditure within rural India. The other variables maintain their definitions from equation (2).

We note that the incidence of paid employment responds very differently to road construction depending on the amenability of local norms to women's employment. Column (1) shows that in *Low Loam* districts, men are more likely to switch to paid work following improvements in road access, while there is a zero net effect for women.[20] Further, from column (5) we can infer that men shift away from being engaged solely in domestic work towards paid employment, so the change is not just a reallocation of casual workers. But we find no significant change in this dimension for women.[21] Several explanations are possible for this phenomenon. For one, Aggarwal (2018) demonstrates that adolescents and young adults drop out of formal education and shift towards paid employment, such as in retail. Shamdasani (2021) establishes that workers in agriculture shift away from subsistence farming towards market-oriented farming, i.e. they switch from household farms to paid labour on large farms. The reason for a gendered effect in employment might well be because men are able to take advantage of road connectivity by seeking—and perhaps finding—jobs in nearby areas outside their village, which might not be a feasible option for women as they bear the dual burden of employment and domestic tasks. The notion of non-hyperlocal employment follows the work of Asher and Novosad (2020), who find that PMGSY roads led to higher employment only in villages that were close to

[20]Running a post-estimation test with the null hypothesis $\beta_1 + \beta_3 = 0$ returns a p-value of 0.911. Hence, we fail to reject the hypothesis that roads had no net effect on women's paid employment.

[21]This time the post-estimation test with the null hypothesis $\beta_1 + \beta_3 = 0$ returns a p-value of 0.305, i.e. we cannot reject the null.

urban areas. Taken together, these results suggest two things. First, fertility rose in *Low Loam* districts due to a contemporaneous roads-induced increase in male employment. The result on fertility is also consistent with the work of (Adsera & Menendez 2011) and (Aksoy 2016) who find, albeit in developed economies, that fertility has a negative relationship with male unemployment. Second, improvements in child health investments are a likely consequence of the income effect subsequent from increased employment.

In stark contrast, column (2) shows that in *High Loam* districts male employment remains unresponsive, while female labour force participation drops by 0.4 percentage points for each percentage point increase in road access. This exacerbates the substantial pre-existing gender gap in paid employment—women are 67 percentage points less likely to be engaged in paid work—in these districts. Similarly, from column (6) we see that women actively substitute away from employment towards full-time domestic work. As such, FLFP actually declines in these districts following the advent of new roads. Prior work has shown that reductions in FLFP intensifies the bargaining power asymmetry within Indian households (Dyson & Moore 1983). Moreover, there is evidence that Indian men prefer more children than less (Eswaran 2006). In this context, we assert that the rise in fertility may simply be reflective of increased male dominance in household decision-making. Meanwhile, dropping out of the labour force relaxes the "budget" constraint faced by women in the time allocation problem between labour, leisure and household work (Becker et al. 1960) and reduces the opportunity cost of childbearing (Schultz 2006). Since mothers prefer larger investments into children to ensure their survival (Eswaran 2006), it follows that increased availability of time enables them to carry out these investments—such as more breastfeeding and immunization visits—that are reflected in lower infant mortality rates.

Our results extend the scope of prior work on rural roads and employment. Asher and Novosad (2020) use a discontinuity design on a village-level dataset—spanning all of India—and find no significant evidence of changes in employment following local road construction from PMGSY. On the other hand, Lei et al. (2019) find that the availability of paved roads in the village leads to a rise in female labour force participation in regions with more gender-equal social norms. Our analysis differs in its identification strategy, since we leverage district-level variation in access to paved roads. As such, we offer a view into the effects of rural roads on employment at a greater degree of agglomeration, which can explain the differences in results. Notably, Aggarwal (2018) uses the same empirical strategy and her results on a country-wide sample suggest that roads do not affect either male or female employment. We are able to reconfirm this finding, i.e. the observed effects from splitting the sample disappear in the full sample consisting of both *Low Loam* and *High Loam* districts. This underscores the importance of local norms on FLFP as a mediator of the gains (or losses) to employment from the advent of paved roads, since divergent effects across subgroups can produce a null effect in the aggregate.

5.2 Household Expenditure

Looking at impacts on household expenditure is non-trivial because two conflicting effects could manifest. On one hand, the higher investments by households into their children's health may reduce the need to seek institutional care, which can reduce medical spending. On the other hand, higher medical expenditure, possibly due to easier access to care, may be a contributor to the observed subsequent decline in infant mortality.

The drop in infant mortality also motivates an inquiry into how household expenditure on medical items, such as hospital bills and medication, changes in the aftermath of road construction. In Panel B in Table 4 we present the results pertaining to medical expenditure, which is expressed as percentage of annual per-capita expenditure (APCE). From columns (1) and (2) we find that road growth is associated with a 2.96 percentage point drop in medical expenditure in *Low Loam* districts, and a smaller drop of 1.2 percentage points in *High Loam* districts. This decline does not necessarily represent lower expenditure in nominal terms. After all, this could simply arise if medical expenditure grew less than the APCE. To that end, in columns (3) and (4) we assess how the natural log of the latter responded to improved road connectivity. We find no evidence of a change in APCE. Assuming that household preferences towards saving and consumption remain unchanged, this suggests that household incomes were unaffected by the provision of all-weather roads. Taken together, the results from columns (1) through (4) establish that households reduced their spending on medical goods and services.

Several factors could be responsible for this phenomenon. For instance, the higher investments by households into their children's health may reduce the need to seek institutional care, which can reduce medical spending. Though our data on these outcomes pertains to a later timeline, Aggarwal (2021) shows that both uptake of antenatal care and immunization also rose in response to roads built under the PMGSY during its initial years. On the other hand, reductions in medical expenditure may also be driven by increased affordability of care, such as through the government-sponsored health schemes like the Janani Suraksha Yojana (JSY) that provided cash payments to women as incentives to seek institutional assistance during childbirth. However, we have little reason to believe that these schemes affected affordability of care in extant health centres differently for districts with different soil types. But even if healthcare did not become universally cheaper for residents of *Low Loam* districts, it is possible that rural roads helped them access health institutions with cheaper care. Aggarwal (2021) finds that households are more likely to use public healthcare following the provision of PMGSY roads. This is relevant because using public healthcare reduces these households' out-of-pocket expenditure. Therefore, if rural roads facilitate greater access to public healthcare for residents of *Low Loam* districts than their *High Loam* counterparts, then we might expect that the reduction in medical expenditure is at least partly due to increased affordability.

5.3 Access To Public Healthcare

Next, we ask whether rural roads reduced the transport barriers faced by households in accessing government healthcare. This is straightforward because the NFHS Woman Questionnaire includes this question[22]. Columns (5) and (6) of Panel B in Table 4 illustrate the results. Before describing the result, we must add a caveat: the specification we use is akin to equation (1), but we are now limited to only one time period — the interview year.[23] This naturally restricts us from using district-specific fixed effects, in lieu of which we use state fixed effects. With this caveat in mind, we find that in *Low Loam* each percentage point of road growth led to a 2.4 percentage point drop in the probability of a woman reporting that government healthcare was too far. A much smaller and non-significant decrease of 0.2 percentage points in this probability is observed for *High Loam* districts. This lends credence to our argument in the preceding subsection, i.e. medical expenditure decreases more in *Low Loam* districts because rural roads enable easier access to public healthcare. As

[22]Question 57 from the Household Questionnaire was used here. The survey text reads "Why don't members of your household generally go to a government facility when they are sick?".

[23]This is because the NFHS is a cross-sectional survey, and each district was surveyed exclusively in either 2015 or 2016.

an aside, this can also explain the increased uptake of child vaccination.

6 Discussion and Conclusion

This paper investigates the impact of road infrastructure on both childbirth and childcare. First, we establish that the provision of paved rural roads causes a tangible increase in fertility and that this effect is much more pronounced over the long term. To the best of our knowledge, this is a novel finding. Further, we use local soil texture to proxy for heterogenous norms on female labour force participation (FLFP) and find that these norms affect the intensity of and reason behind the fertility response. Districts with shallower tillage (*Low Loam*) feature greater involvement of women in agriculture and hence, higher FLFP. Against this backdrop, we find that the advent of all-weather roads engenders higher male employment without any change in FLFP. Hence, we posit that fertility rises in *Low Loam* districts due to reductions in male unemployment.

A different story develops in districts with deeper tillage (*High Loam*), which already exhibit lower levels of FLFP. Herein an improvement in road connectivity leads to women dropping out of the labour force and engaging solely in domestic work. Meanwhile male employment remains unchanged, which means that access to paved roads widens the higher unconditional gender gap in employment within *High Loam* districts. Consequently, with women switching to purely domestic work, the fertility increase can be attributed to women having more time available for childcare.

For childcare, we extend the scope of outcomes and linkages studied in the literature. While Aggarwal (2021) shows the short-term effect of rural roads on child healthcare, we focus on the long-term effects. We also demonstrate the importance of local norms around FLFP as determinants of these effects. Higher levels of FLFP lead to women having greater intra-household bargaining power (S. Anderson & Eswaran 2009), which can produce larger investments in child health (Schultz 2001; Koolwal & Van de Walle 2013). Essentially, we ask whether children born in regions with relatively higher FLFP enjoy larger healthcare investments following the construction of rural roads. Our results attest that this is indeed the case, with children born in *Low Loam* districts benefiting from greater increases in breastfeeding and vaccination than their *High Loam* counterparts. We also show that these investments translate into reductions in infant mortality.

From a policy perspective, the effects of roads on child healthcare clearly provide evidence for positive social externalities. These benefits are likely to compound over time, since better health translates into improved educational attainment (Alderman et al. 2006; Bobonis et al. 2006) and labour supply (Baird et al. 2016), which has implications for both spatial and intergenerational mobility (Ahlburg 1998). Our results on fertility, however, indicate that specifically increases in road connectivity and more generally, access to public infrastructure may have implications for the 'demographic transition' process. If improvements in the 'quality' of children through reduced mortality and increased health investments do not coincide with lower fertility, the benefits from these improvements may be dampened. Other studies document this phenomenon in the context of India. Bhattacharjee and Dasgupta (2019) show that a large-scale malaria eradication scheme reduced child mortality and simultaneously increased fertility, and Nandi and Laxminarayan (2016) find that a policy promoting institutional births increased the probability of childbirth and pregnancy. On the other hand, Nandi, Suman, et al. (2022) show that policies that promote child immunization (such as the Universal Immunization Program in India that they study) might aid the demographic transition by causing a reduction in fertility. Our study adds to this growing literature, and highlights the need to study the varied consequences of massive public infrastructure policies such as the PMGSY. Thus, while highlighting apparent measurable gains, further inquiry needs to consider the multitude of intended and unintended consequences of schemes that provide access to public infrastructure at scale.

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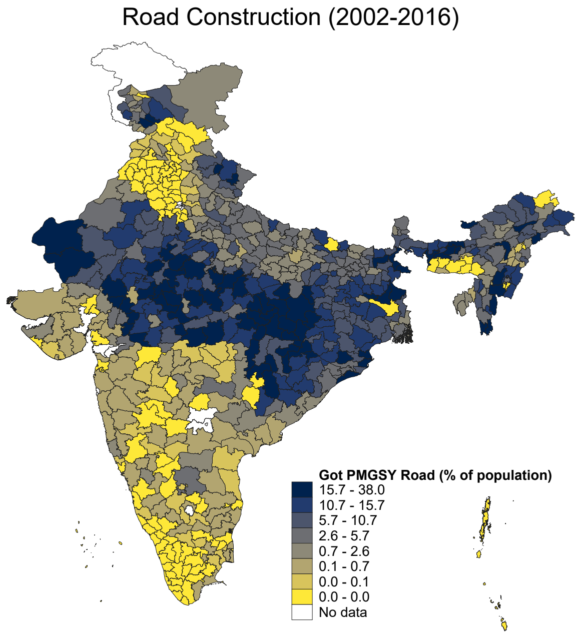
Figures and Tables

Table 1: Sample averages of health outcomes and covariates by soil texture of district

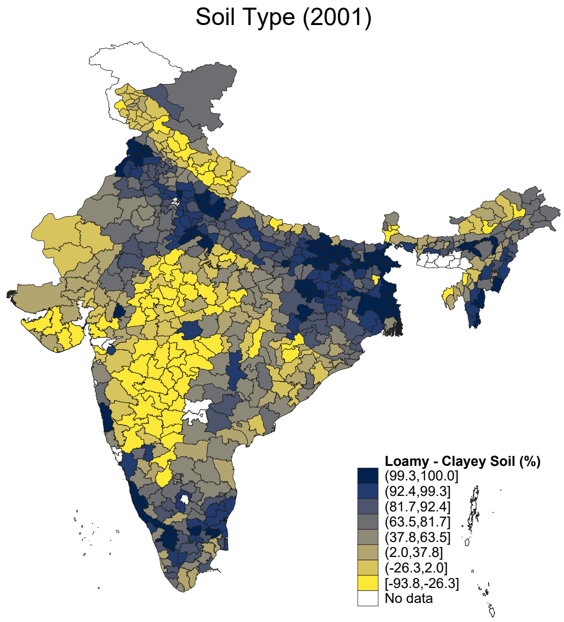
	All Districts	Low Loam	High Loam	(Low-High)
Panel A: Health and maternal care (NFHS-4)				
Fertility (total births / years in reference period)	0.1426	0.1399	0.1464	-0.0065***
Infant mortality	0.0488	0.0471	0.0523	-0.0052**
Adequate food (age 0-23 months)	0.5916	0.5831	0.5978	-0.0147
Breastfeeding duration (months)	15.2578	15.1316	15.4589	-0.3273
Vaccine index	9.4491	9.4860	9.4034	0.0826
Height-For-Age z-score (age 0-5 years)	-1.4342	-1.4197	-1.4722	0.0526
Weight-For-Age z-score (age 0-5 years)	-1.5062	-1.5220	-1.5095	-0.0125
Members in household	6.3737	6.3812	6.3998	-0.0186
Household wealth quintile (1=poorest, 5=wealthiest)	2.5590	2.5812	2.4825	0.0987
Household food consumption index (higher = better)	-0.0031	-0.0195	0.0015	-0.0210
Household treats drinking water	0.3724	0.4429	0.2844	0.1584***
Hindu household	0.7448	0.7814	0.7213	0.0601**
Muslim household	0.1204	0.1212	0.1235	-0.0023
SC or ST household	0.4188	0.4128	0.4137	-0.0009
Female head of household	0.1140	0.0959	0.1275	-0.0316***
Mother completed primary education	0.4700	0.4598	0.4711	-0.0113
Mother completed secondary education	0.1616	0.1474	0.1685	-0.0211**
Mother completed tertiary education	0.0615	0.0563	0.0643	-0.0080
Total children ever born to woman	2.2284	2.1967	2.2714	-0.0747**
Woman's age at first childbirth (years)	20.2505	20.1806	20.2535	-0.0729
Woman's bmi as % of who reference median	118.1248	117.6351	118.2171	-0.5820
Distance to healthcare facility was an issue	0.6580	0.6618	0.6564	0.0055
Govt. healthcare was too far	0.4579	0.4505	0.4739	-0.0234**
Govt. healthcare was of poor quality	0.4653	0.4540	0.4840	-0.0299**
Population with road access at baseline (%)	55.5423	56.7992	54.7056	2.0936
Population that received PMGSY road until 2016 (%)	5.4929	6.0433	5.2949	0.7484
Panel B: Employment and expenditure (NSS Rounds 61-68)				
Share of people with paid employment	0.5159	0.5352	0.4936	0.0416***
Share of women with paid employment	0.2084	0.2428	0.1742	0.0686***
Share of women involved only in household work	0.3185	0.2801	0.3691	-0.0890***
Person's age (years)	27.0144	27.3130	26.7653	0.5477**
Share of agricultural households	0.5996	0.6300	0.5923	0.0376***
Household size	5.6494	5.5611	5.7541	-0.1930***
Log(Annual household expenditure on all items)	19861.3947	19425.0479	19778.6070	-353.5591
Share of annual expenditure on medical items	1.8328	1.9251	1.8018	0.1233

Notes: For each district *d*, the % share of (loamy - clayey) soil is computed. This is compared to the median level of (loamy - clayey) soil across all districts. The soil dummy is coded as 1 if a district's share of (loamy - clayey) soil is above median. Otherwise, it is set to 0. | Source: Soils of India (2001), NFHS-4 (2015-16) and PMGSY data (SHRUG) | * 0.1 ** 0.05 *** 0.01

Figure 1: (A.) District-wise breakdown of road growth and soil type

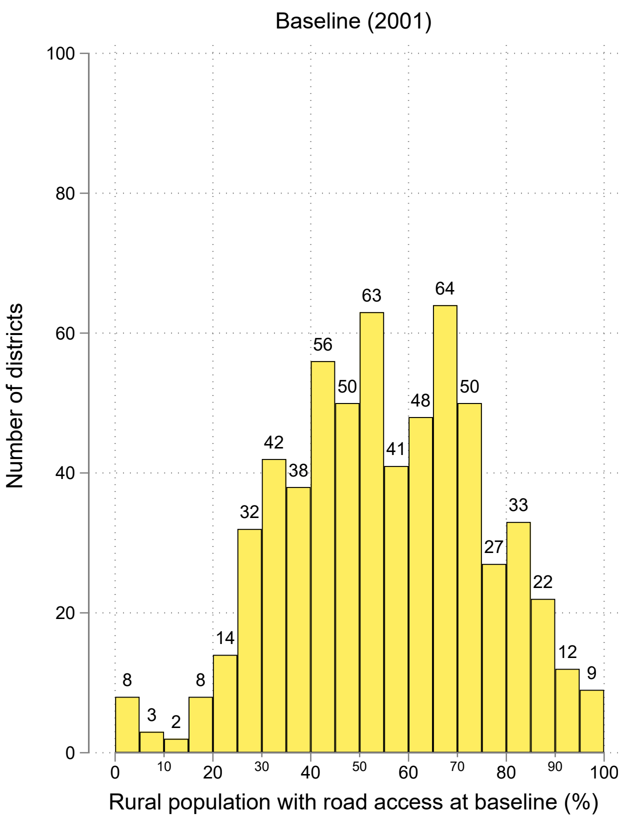


Note: Road Growth is the percentage of rural district residents that received a PMGSY road.



Note: Higher values indicate greater loam and lower clay content.
The median difference in between the share of loamy soil and clayey soil is 63.5%.

(B.) Distribution of baseline road access and road growth



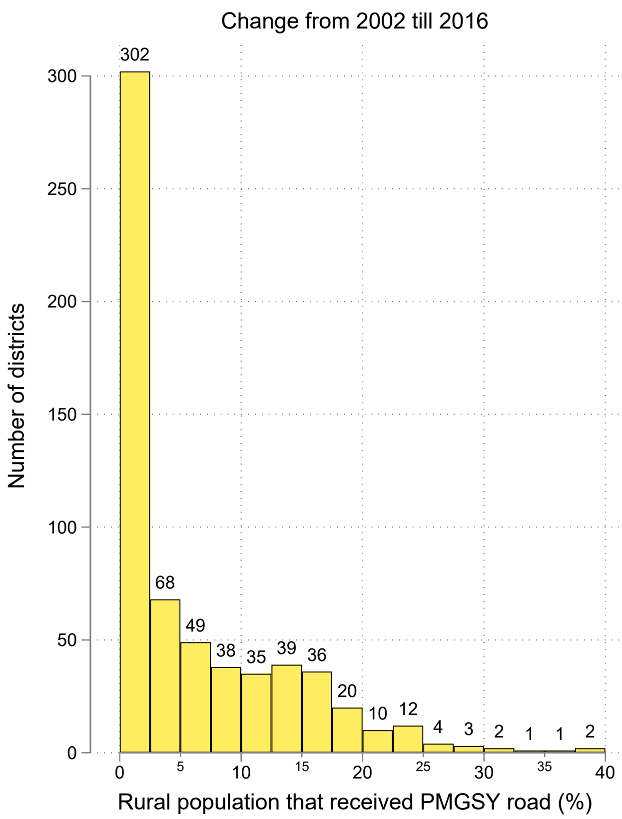


Table 2: Impact of Road Construction on Fertility

Panel A:	Fertility (2002-16)			Fertility (2010-16)		Fertility (1998-00)	
Ages 16-41	All	Low Loam	High Loam	Low Loam	High Loam	Low Loam	High Loam
Road Growth	0.0013***	0.0011***	0.0014***	0.019***	0.015***	0.0053	0.018
	(0.00029)	(0.00035)	(0.00045)	(0.0027)	(0.0023)	(0.014)	(0.017)
Observations	3970469	1906558	1970789	793683	827482	271263	277048
Outcome Mean	0.13	0.12	0.14	0.11	0.12	0.17	0.19
Outcome Std. Dev.	0.34	0.33	0.34	0.31	0.33	0.38	0.39
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B:	Total Births (2002-16)			Total Births (2010-16)		Total Births (1998-00)	
Ages 16-49	All	Low Loam	High Loam	Low Loam	High Loam	Low Loam	High Loam
Road Growth	0.00090***	0.00063**	0.0011***	0.016***	0.013***	0.0062	0.018
	(0.00027)	(0.00031)	(0.00044)	(0.0022)	(0.0020)	(0.015)	(0.018)
Observations	4327189	2080149	2144911	949523	984423	271263	277048
Outcome Mean	0.12	0.11	0.13	0.094	0.10	0.17	0.19
Outcome Std. Dev.	0.33	0.32	0.33	0.29	0.31	0.38	0.39
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* 0.1 ** 0.05 *** 0.01 | **Notes**: All specifications use District FE, a Linear Time Trend and District-level Linear Time Trends. Standard errors are clustered at the district level. | *Fertility* is a binary outcome takes value=1 for woman w in year y if she gave a birth during that year, and 0 otherwise.

Table 3: Impact of Road Construction on Child Healthcare

Panel A: Main Sample	Breastfeeding (Months)		Vaccination Index		Infant Mortality	
	Low Loam	High Loam	Low Loam	High Loam	Low Loam	High Loam
Road Growth	2.08***	1.43***	1.70***	1.38***	-0.022***	-0.0085***
	(0.30)	(0.32)	(0.55)	(0.33)	(0.0040)	(0.0025)
Observations	64872	72435	84022	96311	72562	83940
Outcome Mean	15.8	16.4	10.7	11.0	0.052	0.059
Outcome Std. Dev.	12.5	13.0	56.0	55.0	0.22	0.24
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Placebo Test	Breastfeeding (Months)		Vaccination Index		Infant Mortality	
	Low Loam	High Loam	Low Loam	High Loam	Low Loam	High Loam
Road Growth	0.13	0.15	0.36	-0.54	-0.0021	0.0033
	(0.15)	(0.19)	(0.67)	(1.09)	(0.0054)	(0.0081)
Observations	22776	26741	22885	26861	18661	22275
Outcome Mean	15.2	15.5	-30.5	-48.4	0.10	0.11
Outcome Std. Dev.	9.85	10.1	81.9	79.9	0.30	0.31
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

* 0.1 ** 0.05 *** 0.01 | **Notes**: All specifications use Birth Month FE, District FE, a Linear Time Trend and District-level Linear Time Trends. Standard errors are clustered at the District level. | *Adequate Food* is a binary outcome for children aged 6-23 months. It takes value = 1 if the child either received two meals a day (and was breastfed) or received three meals (and was not breastfed), and 0 otherwise. *Breastfeeding Duration* is a discrete outcome that records, for each child, the number of months he or she was breastfed. The *Vaccine Index* is a composite indicator that is computed via an Inverse Covariance Weighting (ICW) of multiple vaccine indicators present within the NFHS data. These indicators are first standardized, and then their ICW matrix is used to calculate the Vaccine Index score. The indicators cover vaccines for: Measles, Tetanus, Diptheria, Polio (3 shots); along with records of Vitamin-A supplements. *Infant Mortality* is a binary outcome. It takes value = 1 if the child died within the first 12 months of birth, and 0 otherwise.

Table 4: Impact of Road Construction on Employment, Expenditure and Healthcare Access

Panel A:	Paid Employment		Agricultural Work		Only HH Work	
Employment Patterns	Low Loam	High Loam	Low Loam	High Loam	Low Loam	High Loam
Road Growth	0.0055**	0.0024	0.0059**	0.0015	-0.0093**	-0.0013
	(0.0023)	(0.0024)	(0.0024)	(0.0027)	(0.0037)	(0.0031)
Female	-0.56***	-0.67***	0.077***	-0.0071	0.19***	0.36***
	(0.011)	(0.011)	(0.0094)	(0.012)	(0.014)	(0.017)
Female × Road Growth	-0.0052***	-0.0040**	-0.0043***	-0.0014	0.013***	0.0096***
	(0.0012)	(0.0018)	(0.0011)	(0.0020)	(0.0019)	(0.0030)
Observations	325921	339375	195636	191151	325921	339375
Outcome Mean	0.56	0.50	0.57	0.48	0.12	0.20
Outcome Std. Dev.	0.50	0.50	0.50	0.50	0.33	0.40
District and Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B:	Medical Exp.		Log(Annual Exp.)		Govt. Healthcare Far	
Expenditure and Access	Low Loam	High Loam	Low Loam	High Loam	Low Loam	High Loam
Road Growth	0.00064*	-0.0014***	0.0042	0.014	-0.0025**	-0.00026
	(0.00038)	(0.00047)	(0.014)	(0.0087)	(0.0012)	(0.0013)
Observations	130284	135689	130284	135689	51392	73722
Outcome Mean	0.021	0.018	8.98	9.01	0.45	0.49
Outcome Std. Dev.	0.072	0.068	1.13	1.11	0.50	0.50
District and Time FE	Yes	Yes	Yes	Yes	No	No
State and Time FE	No	No	No	No	Yes	Yes

* 0.1 ** 0.05 *** 0.01 | **Notes**: All specifications in Panel A and Columns (1) through (4) of Panel B use Month FE, District FE, a Linear Time Trend and District-level Linear Time Trends. Only Columns (5) and (6) of Panel B use State FE, a Linear Time Trend and State-level Linear Time Trends. Standard errors are clustered at the district level. | *Employed* is a binary variable that is set = 1 if the respondent is engaged in paid employment at the time of survey and 0 otherwise. *Agricultural Work* is a binary variable that is set = 1 if the respondent worked for pay in the agricultural sector at the time of survey, and 0 if they worked for pay elsewhere. *Only HH Work* is a binary variable that takes value = 1 if the respondent undertakes only unpaid household work, and 0 otherwise. Both variables are set to missing for respondents who chose the following categories: Pensioners / Rentiers, Unable to work due to disability, Others (begging etc). | *Medical* refers to the household's annual medical expenditure as a share of annual total expenditure. *Log(Annual Expenditure)* refers to the natural log of the household's total annual expenditure on the following categories: medical, schooling and educational articles, clothing and durable goods. *Govt. Healthcare Far* takes value=1 if the woman reported not using government healthcare because it was too far, and 0 otherwise.

Online Appendix

Figure 2: Residualized outcomes across levels of road connectivity

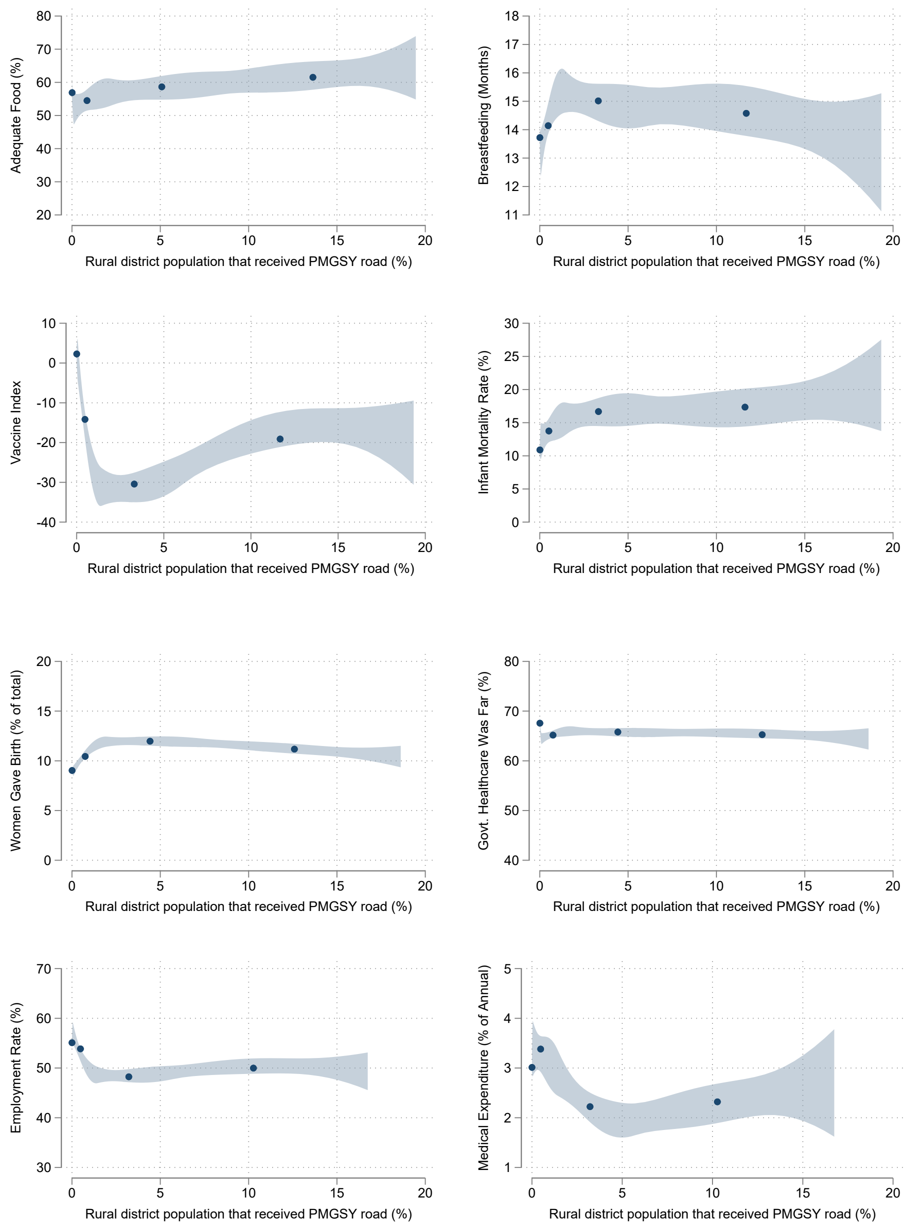


Table 5: Impact of Road Construction on Employment (Placebo)

	Paid Employment		Agricultural Work		Only HH Work	
	Low Loam	High Loam	Low Loam	High Loam	Low Loam	High Loam
Road Growth	0.0042	0.0016	0.00048	-0.0066	-0.0039	-0.0071
	(0.0035)	(0.0073)	(0.0056)	(0.010)	(0.0051)	(0.012)
Female	-0.54***	-0.67***	0.12***	0.075***	0.16***	0.35***
	(0.014)	(0.014)	(0.011)	(0.011)	(0.015)	(0.021)
Female × Road Growth	-0.0016	-0.0020	-0.0077***	-0.0024	0.0050*	0.0016
	(0.0022)	(0.0028)	(0.0019)	(0.0033)	(0.0026)	(0.0056)
Observations	98481	133754	52710	64542	98481	133754
Outcome Mean	0.59	0.51	0.66	0.60	0.091	0.18
Outcome Std. Dev.	0.49	0.50	0.47	0.49	0.29	0.38
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

* 0.1 ** 0.05 *** 0.01 | **Notes**: All specifications use Quarter FE, Stratum FE, a Linear Time Trend and Stratum-specific Linear Time Trends. Both panels *Employed* is a binary variable that is set = 1 if the respondent is engaged in paid employment at the time of survey and 0 otherwise. *Agricultural Work* is a binary variable that is set = 1 if the respondent worked for pay in the agricultural sector at the time of survey, and 0 if they worked for pay elsewhere. *Only HH Work* is a binary variable that takes value = 1 if the respondent undertakes only unpaid household work, and 0 otherwise. Both variables are set to missing for respondents who chose the following categories: Pensioners / Rentiers, Unable to work due to disability, Others (begging etc).

Table 6: Impact of Road Construction on Child Health Investments across Birth Order

	Breastfeeding (Months)		Vaccination Index		Infant Mortality	
	Low Loam	High Loam	Low Loam	High Loam	Low Loam	High Loam
Road Growth	2.08***	1.46***	1.85***	1.49***	-0.023***	-0.0078***
	(0.30)	(0.32)	(0.56)	(0.35)	(0.0040)	(0.0026)
Birth Order	0.47***	0.33***	-1.09***	-2.14***	0.0047**	0.0065***
	(0.099)	(0.060)	(0.38)	(0.38)	(0.0021)	(0.0015)
Road Growth × Birth Order	-0.0056	-0.0093*	-0.048	-0.040	-0.000025	-0.00027*
	(0.0057)	(0.0052)	(0.030)	(0.044)	(0.00016)	(0.00014)
Observations	64872	72435	84022	96311	72562	83940
Mean of Dep. Variable	15.8	16.4	10.7	11.0	0.052	0.059
SD of Dep. Variable	12.5	13.0	56.0	55.0	0.22	0.24
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

* 0.1 ** 0.05 *** 0.01 | **Notes**: Fixed Effects refer to Birth Month FE, District FE and District-level linear time trends. Standard errors are clustered at the District level. | *Breastfeeding Duration* is a discrete outcome that records, for each child, the number of months he or she was breastfed. The *Vaccine Index* is a composite indicator that is computed via an Inverse Covariance Weighting (ICW) of multiple vaccine indicators present within the NFHS data. These indicators are first standardized, and then their ICW matrix is used to calculate the Vaccine Index score. The indicators cover vaccines for: Measles, Tetanus, Diptheria, Polio (3 shots); along with records of Vitamin-A supplements. *Infant Mortality* is a binary outcome. It takes value = 1 if the child died within the first 12 months of birth, and 0 otherwise.

Table 7: Impact of Road Construction on Fertility (with Village Fixed Effects)

	Fertility (2002-16)			Fertility (2010-16)		Fertility (1998-00)	
	All	Low Loam	High Loam	Low Loam	High Loam	Low Loam	High Loam
Road Growth	0.0012***	0.0011***	0.0013***	0.020***	0.015***	-0.00026	0.016
	(0.00018)	(0.00024)	(0.00026)	(0.0011)	(0.00087)	(0.015)	(0.016)
Observations	4051637	1946403	2009809	809793	843504	277483	282844
Outcome Mean	0.13	0.12	0.14	0.11	0.12	0.17	0.19
Outcome Std. Dev.	0.34	0.33	0.34	0.31	0.33	0.38	0.39
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* 0.1 ** 0.05 *** 0.01 | **Notes**: All specifications use Village FE, a Linear Time Trend and Village-level Linear Time Trends. Standard errors are clustered at the village level. | *Fertility* is a binary outcome takes value=1 for woman w in year y if she gave a birth during that year, and 0 otherwise. All specifications include the following controls: woman's age (years), household size, wealth index score, caste, religion, electricity access at home, cooking fuel (LPG or natural gas), access to piped water, access to treated water, total children ever born to the woman, age at which she first gave birth and whether the household is headed by a woman.

Table 8: Impact of Road Construction on Child Healthcare (with Village Fixed Effects)

	Breastfeeding (Months)		Vaccination Index		Infant Mortality	
	Low Loam	High Loam	Low Loam	High Loam	Low Loam	High Loam
Road Growth	1.96***	1.41***	2.21***	1.03***	-0.023***	-0.0070***
	(0.20)	(0.13)	(0.71)	(0.39)	(0.0050)	(0.0022)
Observations	64683	72272	83873	96195	72341	83767
Outcome Mean	15.8	16.4	10.7	11.0	0.052	0.059
Outcome Std. Dev.	12.5	13.0	56.0	55.0	0.22	0.24
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

* 0.1 ** 0.05 *** 0.01 | **Notes**: All specifications use Birth Month FE, Village FE, a Linear Time Trend and Village-level Linear Time Trends. Standard errors are clustered at the village level. | *Breastfeeding Duration* is a discrete outcome that records, for each child, the number of months he or she was breastfed. The *Vaccine Index* is a composite indicator that is computed via an Inverse Covariance Weighting (ICW) of multiple vaccine indicators present within the NFHS data. These indicators are first standardized, and then their ICW matrix is used to calculate the Vaccine Index score. The indicators cover vaccines for: Measles, Tetanus, Diptheria, Polio (3 shots); along with records of Vitamin-A supplements. *Infant Mortality* is a binary outcome. It takes value = 1 if the child died within the first 12 months of birth, and 0 otherwise.

Table 9: Impact of Road Construction on Fertility by Subgroup

	Fertility x Education		Fertility x Caste		Fertility x Income	
	Low Loam	High Loam	Low	High	Low	High
Road Growth	0.00074**	0.00075*	0.00096***	0.0013***	0.00082**	0.00075*
	(0.00033)	(0.00044)	(0.00036)	(0.00047)	(0.00033)	(0.00044)
Road Growth × Primary Educ.	0.0015***	0.0021***				
	(0.00016)	(0.00021)				
Road Growth × Secondary Educ.	0.00063***	0.0015***				
	(0.00013)	(0.00024)				
Road Growth × Tertiary Educ.	0.0010***	0.0013***				
	(0.00021)	(0.00029)				
Road Growth × SC/ST HH			0.00029***	0.00019*		
			(0.000092)	(0.00010)		
Road Growth × Wealth Quintile					0.00012***	0.00032***
					(0.000044)	(0.000063)
Observations	1946403	2009809	1946403	2009809	1946403	2009809
Outcome Mean	0.12	0.14	0.12	0.14	0.12	0.14
Outcome Std. Dev.	0.33	0.34	0.33	0.34	0.33	0.34
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

* 0.1 ** 0.05 *** 0.01 | **Notes**: All specifications use District FE, a Linear Time Trend and District-level Linear Time Trends. Standard errors are clustered at the district level. | *Fertility* is a binary outcome takes value=1 for woman w in year y if she gave a birth during that year, and 0 otherwise.