Pathways to Progress: The Complementarity of Bicycles and Road Infrastructure for Girls' Education*

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Abstract

In which settings can bicycles help to improve girls' education in low-income countries? This paper analyzes the complementarity between all-weather roads and a bicycle program in India aimed at increasing girls' secondary school enrollment. Using a triple-difference strategy, I find that the program benefits girls living 3–10 km away from schools with all-weather road connections, increasing their enrollment by 60 percent and reducing the gender enrollment gap by 51 percent. There are no effects for girls in villages without all-weather roads or girls living more than 10 km from school. The findings emphasize the importance and interdependence of road infrastructure, mode of transport, and distance to school for improving girls' education in India.

Keywords: Roads, Bicycles, Infrastructure, Girls' Education, Gender Education Gap, India

JEL codes: O18, I21, I28, H42, J16

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1 Introduction

Equal access to education and gender equality are two fundamental United Nations Development Goals, which call for the same opportunities for male and female students to go to school (UN General Assembly, 2015). Nevertheless, female students in low- and middle-income countries still face several barriers to obtaining the same level of educational attainment as male students (Glewwe *et al.*, 2020). Important barriers, among others, are the proximity to school (Muralidharan and Prakash, 2017; Fiala *et al.*, 2022), safety (Borker, 2021), and cultural norms (Jayachandran, 2015). Combined with the importance of education for economic outcomes, such as earnings (Psacharopoulos and Patrinos, 2018) and economic growth (Hanushek and Woessmann, 2008, 2012), it is therefore of major interest to understand the effectiveness and scalability of education policies that aim to reduce the remaining barriers for female students.

In this paper, I study a bicycle program in Bihar (Mukhyamantri Balika Cycle Yojana), India, with the goals of increasing secondary school enrollment and fostering empowerment among female adolescents. In particular, I analyze the complementarity of the bicycle program and all-weather roads as a potential factor to drive the program's success. The average distance to secondary school at the start of the bicycle program was above 5 km, creating large barriers for female students to attend secondary school since social norms in India, such as safety and purity concerns often restrict their mobility to other villages (Jayachandran, 2015).[1] As a response, starting in 2006, the government of Bihar provided each girl who enrolled in secondary school (9th grade) with 2000 rupees to buy a bicycle. The transfer was allocated in public ceremonies hosted by the secondary schools, which created social pressure for parents to conform to the program (Muralidharan and Prakash, 2017).[2]

Earlier research indicates that the bicycle program was implemented effectively and successfully reduced the gender school enrollment gap in Bihar. Ghatak *et al.* (2016) show that the leakages of the program were below 5 percent while Muralidharan and Prakash (2017) find that the bicycle program increased the secondary school enrollment rate of girls by 32 percent. The effect comes from girls living at least 3 km (median distance) away from secondary school, suggesting that the reduction of distance costs was the main driver of the program's impact.

Nonetheless, little is known about the complementarity of road infrastructure and the bicycle program. One important element of the program's success might have been the connectivity of rural villages to

[1] See Table A1 in the Appendix for more details.

[2] For an extensive program description, see Muralidharan and Prakash (2017).

all-weather roads. As opposed to dry-season roads or small footpaths, all-weather roads are expected to be functional throughout the year, especially in the rainy season (monsoons), and connect villages to the nearest schools and labor markets (Mukherjee, 2012). Considering the human capital decision of girls in Bihar, having a bicycle in combination with being connected to an all-weather road brings several advantages when traveling to school. First, travel time and distance costs to school are reduced even further compared to riding a bicycle on dry-season roads or small footpaths, especially in regions with difficult terrain. Second, all-weather roads might improve girls' and parents' perception of safety, which can directly impact the decision to attend school.[3] Third, all-weather roads make schools more accessible throughout the year as they withstand more extreme weather conditions. This is particularly relevant during monsoons, which stay for several months, cause heavy rainfall, and prevent access to school from dry-season roads. Overall, the combination of all-weather roads and bicycles should increase the net benefits of attending school compared to just obtaining a bicycle.[4]

I use three data sources to study the interdependence of all-weather roads and the bicycle program. The first and main data source is the District Level Household and Facility Survey 3 (DLHS-3) ([dataset] International Institute for Population Sciences (IIPS), 2010), which is a nationally representative household survey conducted shortly after the start of the bicycle program in Bihar. DLHS-3 contains detailed information on household members and village infrastructure, which makes it suitable to investigate the complementary effect of bicycles and all-weather roads on secondary school enrollment. The second data source is the District Level Household and Facility Survey 2 (DLHS-2) ([dataset] International Institute for Population Sciences (IIPS), 2006), which contains similar information on household members and village infrastructure before the introduction of the program. I use DLHS-2 to assess the parallel trend assumption pre-treatment. The third data source is the Indian Human Development Survey (IHDS) ([dataset] Desai *et al.*, 2018). The main advantage of IHDS is the detailed information on regular school attendance, crime, and the provision of public street lights, which I can use to investigate potential mechanisms.

To identify the complementarity of road infrastructure and bicycles, I employ a triple-difference estimator and perform a sub-sample split by all-weather road connectivity. Similar to Muralidharan and Prakash (2017) and Mitra and Moene (2017), I use boys in the state of Bihar and boys and girls in the neighboring state Jharkhand as natural comparison groups to isolate the effect of the bicycle program. To

[3] Borker (2021) shows that safety concerns affect the human capital decision of women in India and the route of travel they choose to go to college. Jain and Biswas (2021) show that the construction of paved all-weather roads reduces crime rates and the risk of sexual harassment in rural India, partly due to improved street lights and better employment opportunities.

[4] While the connectivity of villages to the nearest labor markets potentially increases the opportunity costs of going to school, the bicycle transfer is conditional on enrolling in school. Therefore, working in another village or town might not be a feasible option without a bicycle, especially in light of women's restricted mobility in India.

mitigate concerns about the validity of the all-weather road sub-sample split, I show that it is not driven by other competing mechanisms, does not show any trends before the start of the program, and is not confounded by other policies in Bihar happening during the same time as the intervention.

The results indicate that girls in the treatment cohort in Bihar who lived at least 3 km away from secondary school and whose villages are connected to an all-weather road experienced an increase in secondary school enrollment by 46.6 percent, reducing the respective gender education gap by around 48.5 percent. On the other hand, I find no effect for girls who live at least 3 km away and whose villages are not connected to an all-weather road. Together, the results emphasize that all-weather roads are not just enhancing the bicycle program's impact (partial complementarity) but are a precondition for its success (perfect complementarity).

Investigating the mechanisms behind the importance of all-weather roads for the program, I find the reduction of distance costs to be the main driver. The bicycle program only benefits girls living 3–10 km away from school with an all-weather road connection, confirming the inverted U-shape pattern found by Muralidharan and Prakash (2017) and emphasizing the interdependence of all-weather roads, bicycles, and distance to school for girls' education. For this subgroup, the bicycle program increased secondary school enrollment by 59.8 percent and reduced the gender education gap by 51.2 percent. Further evidence suggests that other mechanisms, such as differences in the expected days of school attendance and the perception of safety, might explain the crucial role of all-weather roads for the program.

Overall, the findings emphasize the important and interdependent role of infrastructural elements in the accessibility of secondary schools and the improvement of girls' education in India. In line with the O-ring theory by Kremer (1993), each infrastructural element: road infrastructure (all-weather roads), transportation (bicycles), and schools (distance to school) needs to be adequately provided to impact the secondary school enrollment decision of girls.

This paper speaks to the literature on bicycle programs that aim to empower females in low-income settings. Previous studies by Muralidharan and Prakash (2017) (Bihar) and Fiala *et al.* (2022) (Zambia) indicate a positive impact of bicycle programs on girls' education. In addition, Mitra and Moene (2017) shows that girls in Bihar who received bicycles are more likely to complete secondary school, enroll in college, delay marriage, and work in non-agricultural sectors. Kjelsrud *et al.* (2022) also find that bicycle programs can increase the empowerment of females within the same household. The results in this paper identify the main beneficiaries of the bicycle program in Bihar in greater detail, highlight the role of all-weather roads, and emphasize the interdependence of infrastructural elements for the success of such programs.

The findings also add to the literature on road infrastructure and economic development in India. While there is empirical evidence that the construction of all-weather roads shifts village inhabitants out of agriculture (Asher and Novosad, 2020), improves access to healthcare (Aggarwal, 2021), and education (Mukherjee, 2012; Aggarwal, 2018; Adukia *et al.*, 2020), and reduces criminal activities (Jain and Biswas, 2021), I demonstrate that all-weather roads also have a second round effect on the economic development of villages through policies which implicitly rely on well-functioning road infrastructure. In the case of the bicycle program, all-weather roads were crucial to sufficiently reduce the barriers for female students to access secondary school.

Finally, this paper contributes to the extensive literature on school enrollment policies in low-income settings. In general, popular school enrollment policies, such as school construction (Duflo, 2001; Kazianga *et al.*, 2013; Burde and Linden, 2013; Neilson and Zimmerman, 2014) and conditional cash transfers (CCTs) (Schultz, 2004; Attanasio *et al.*, 2010; Glewwe and Kassouf, 2012; Galiani and McEwan, 2013) were found to have a positive impact on school enrollment and reduce the gender education gap. Nonetheless, hiring new teachers, constructing new schools, or targeting and verifying the conditionality lead to high administrative costs, questioning the cost-effectiveness and scalability of such interventions (Benhassine *et al.*, 2015; Muralidharan and Prakash, 2017). The results show that bicycle programs might be a scalable and cost-effective alternative for increasing girls' education if high-quality road infrastructure and nearby schools are provided.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 discusses the empirical strategy. Section 4 shows the results. Section 5 presents robustness checks, and Section 6 concludes.

2 Data

The main data source for the analysis is the District Level Household and Facility Survey 3 (DLHS-3) ([dataset] International Institute for Population Sciences (IIPS), 2010), which includes detailed information about over 700,000 Indian households and their villages (International Institute for Population Sciences (IIPS), 2010a). The DLHS-3 design corresponds to two-stage stratified sampling with villages as the primary sampling unit.[5] The survey was conducted in the second school year after the start of the bicycle

[5]Three-stage stratified sampling in urban areas.

program, allowing me to estimate the interdependence of road infrastructure and bicycles on secondary school enrollment by using the school cohorts just before and after the start of the intervention.[6] Next to socioeconomic background characteristics, DLHS-3 contains information about the highest educational attainment of each household member and the enrollment status for everyone under the age of 18. The village questionnaire includes detailed information on the infrastructure of the villages and distances to education and health facilities. Since the initial purpose of the DLHS-3 was the assessment of the governmental health facilities and the population's accessibility to them, details about the connectivity of villages to an all-weather road are also documented (International Institute for Population Sciences (IIPS), 2010b).

The exact question in the DLHS-3 data is whether the villages have an all-weather road connection to health facilities.[7] While this does not necessarily imply that all-weather roads connect villages to the nearest secondary school, there are good reasons to believe that the information can serve as a reasonable approximation. First, health facilities and high schools in India are often spatially clustered to provide efficient access to basic facilities for a broad range of people (Mishra *et al.*, 2021). Table A2 in the Appendix confirms the clustering of education and health facilities for Bihar and Jharkhand in 2007–2008 using the DLHS-3 data. Villages with a health facility are about three times more likely to have a secondary school compared to villages with no health facility. Second, being connected via an all-weather road implies that villages are connected to the Indian all-weather-road network, even if the nearest village with a health facility does not have a secondary school. Since most villages in Bihar with a secondary school are also connected to all-weather roads, the connection of a village to the all-weather-road network almost surely implies a direct all-weather-road pathway to secondary school.[8] Motivated by the findings, I assess the all-weather road connectivity of villages to secondary schools by constructing a dummy taking on the value 1 if the village is connected by an all-weather road to any type of health facility.[9]

As the main goal of the paper is to understand the mechanism of the bicycle program in greater detail and test for the complementarity of all-weather roads and bicycles, I restrict the sample to boys and girls in Bihar and Jharkhand living at least 3 km (median distance) away from secondary school. They correspond to the main beneficiaries of the program identified by Muralidharan and Prakash (2017).

I additionally use the second phase of the prior conducted District Level Household and Facility Survey

[6] The bicycle program started in June 2006, while DLHS-3 was conducted at the end of 2007 and the start of 2008.

[7] Health facilities include sub-centers, primary health centers, community health centers, or district hospitals.

[8] Table A3 in the Appendix shows that 86.5 percent of the villages with a secondary school in Bihar are connected by an all-weather road.

[9] Note that the dummy takes on the value 0 for any dry-season road or small footpath. Hence, the indicator variable does not measure road connectivity but rather road quality.

2 (DLHS-2) ([dataset] International Institute for Population Sciences (IIPS), 2006) to test for parallel trends in the secondary school enrollment rate across gender, state, and all-weather-road connectivity.[10] One critical advantage of the DLHS-2 data compared to official enrollment data sets is the entailed information about villages' connectivity by all-weather roads, which is necessary to test for pre-trends of the triple difference estimator for each sub-sample. Nevertheless, the DLHS-2 is cross-sectional and only asks respondents about their highest completed grades. Therefore, I can only assess the pre-trend of the ninth-grade completion but not ninth-grade enrollment rate across age cohorts.

To supplement the analysis and investigate potential mechanisms, I also use data from the Indian Human Development Survey (IHDS) ([dataset] Desai *et al.*, 2018). IHDS is a nationally representative household survey (around 42,000 households) conducted in the school year 2004–2005, which contains detailed information on household members, village characteristics, days of absenteeism from secondary school, criminal activity, and participation in public street light programs. I use this information to provide descriptive evidence on the role of expected secondary school attendance and the perception of safety. One important difference to DLHS is that the question in IHDS asks about the connectivity of villages to pucca (paved) or kaccha (non-paved) roads. To set the categorization as close as possible to the all-weather road definition in DLHS-3, I construct a dummy taking on the value 1 if the village is connected to a pucca road. Nevertheless, some kaccha roads, such as gravel roads, also fall under the all-weather road category (Indian Roads Congress (IRC), 2002). Since the comparability only holds up to a certain degree, the results with IHDS mainly serve as descriptive evidence for the role of expected secondary school attendance and the perception of safety.

3 Empirical Strategy

To test for the complementarity of all-weather roads and the bicycle program, I construct a triple difference estimator, which I split by all-weather road connectivity.[11] Exploiting the timing of DLHS-3, I construct treatment and control cohorts based on the expected secondary school entry age in India, which is 14 years. As DLHS-3 was conducted one and a half years after the start of the bicycle program, I follow Muralidharan and Prakash (2017) and define the 16 to 17-year-old girls as the pre-treatment cohort as they are expected to have entered secondary school before the bicycle program started (before June 2006). The

[10] The second phase of the survey took place at the beginning of the school year 2004–2005 for Bihar and Jharkhand (International Institute for Population Sciences (IIPS), 2006).

[11] An alternative estimation strategy is to construct a quadruple difference estimator. The results can be seen in Table A4 in the appendix and are qualitatively similar to the results in Table 3 and Table 4.

14 to 15-year-old girls should have entered ninth grade after the start of the program, therefore resembling the post-treatment cohort. One limitation of this treatment group definition is that it depends on the expected and not actual secondary school entry age. Therefore, I can only estimate the bicycle program's impact on the net secondary school enrollment rate, which is likely a lower-bound estimate of the program's impact on the total secondary school enrollment.[12]

Before I present the estimation strategy to test for the complementarity of road infrastructure and bicycles, it is important to derive the estimator that credibly identifies the impact of the bicycle program. Simply comparing girls' secondary school enrollment rate in Bihar before and after 2006 to assess the intervention would likely be confounded by time-varying factors, since Bihar experienced rapid economic growth and an increase in public education spending in the 2000s (Muralidharan and Prakash, 2017). Constructing a difference-in-difference estimator by adding boys in Bihar as a comparison group would account for time-varying factors under the assumption that girls' and boys' secondary school enrollment rates were affected in the same way. Using DLHS-2, Table A5 in the Appendix shows the difference-in-difference estimator for the ninth-grade completion rate of the age groups from 15 to 17 in Bihar.[13] The results reject the parallel trend assumption and suggest that the respective gender education gap was decreasing in Bihar before the bicycle program was implemented.

To account for the differential trends of girls' and boys' secondary school enrollment rates, I follow Muralidharan and Prakash (2017) by adding boys and girls of the neighboring state Jharkhand as another comparison group. The identifying assumption of the resulting triple difference estimator (DDD) becomes that the gender secondary school enrollment gap across treatment and control states would evolve in parallel terms in the absence of treatment. Table 1 evaluates the plausibility of this assumption for the ninth-grade completion rate in the period before the treatment. Using DLHS-2 data, I fail to reject the parallel trend assumption pre-treatment, which increases the confidence that the DDD method can credibly estimate the bicycle program's impact. The finding is important from an empirical perspective, as it supports the estimation strategy by Muralidharan and Prakash (2017), Mitra and Moene (2017), and Kjelsrud *et al.* (2022) using another data source to test for parallel trends. Nonetheless, the coefficient of the triple interaction term is slightly negative, which implies that the gender secondary school enrollment gap seems to have closed more slowly in Bihar compared to Jharkhand. Therefore, the DDD estimate

[12]A higher rate of students lags behind their age-appropriate grade compared to having skipped one.

[13]Since children in Bihar were expected to be six years old before they enter primary school (Ministry of human resource development, 2005), most children are expected to be at the age of 15 right after ninth grade where DLHS-2 took place (the school year 2004–2005). Therefore, I assign 15-year-olds to the most recent ninth-grade school cohort 2003–2004, 16-year-olds to the 2002–2003 school cohort, and 17-year-olds to the school cohort 2001–2002.

likely provides a lower bound of the bicycle program's impact.

Table 1: Parallel Trend Assumption - Pre-Treatment Test

	Dependent variable: Completed grade 9					
	Whole sample			At least median dist. (≥3 km)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Parallel-trends test for triple-difference setting						
Year × female × Bihar	-0.039	-0.045	-0.036	-0.034	-0.026	-0.022
	(0.029)	(0.027)	(0.026)	(0.035)	(0.032)	(0.033)
Observations	7758	7758	7758	4835	4835	4835
Panel B: Parallel-trends test for triple-difference setting with all-weather road						
Year × female × Bihar	-0.029	-0.048	-0.032	-0.006	-0.012	0.001
	(0.035)	(0.034)	(0.032)	(0.045)	(0.042)	(0.042)
Observations	5113	5113	5113	3041	3041	3041
Panel C: Parallel-trends test for triple-difference setting without all-weather road						
Year × female × Bihar	-0.055	-0.035	-0.033	-0.070	-0.041	-0.039
	(0.042)	(0.038)	(0.039)	(0.046)	(0.041)	(0.042)
Observations	2645	2645	2645	1794	1794	1794
Household level controls	No	Yes	Yes	No	Yes	Yes
Village level controls	No	Yes	No	No	Yes	No
Village fixed effects	No	No	Yes	No	No	Yes

Notes: *p<0.1; **p<0.05; ***p<0.01
Test for parallel trends pre-treatment using the second phase of DLHS-2 (2004–2005). School cohorts are approximated by age groups (15- to 17-year-olds) and the variable year is coded from 0 to 2, taking on the value 2 for the 15-year-old age group (approximate for the school cohort 2003–2004), 1 for the 16-year-old age group (approximate for the school cohort 2002–2003), and 0 for the 17-year-old age group (approximate for the school cohort 2001–2002). The household-level controls include indicators for scheduled castes, scheduled tribes, and other backward castes, as well as dummies for Hindus and Muslims. Furthermore, household head years of schooling, a dummy for household head male, and a PCA index for household assets are entailed. Village-level controls include distance to the bus station, the nearest town, railway station, district headquarters, middle school, and a dummy for middle school in town. Standard errors, clustered at the village level, are in parentheses. Household weights are used to reflect the target population and account for the survey design.

While the DDD estimate assesses the overall impact of the bicycle program in Bihar, I can split the sample by all-weather road connectivity to estimate the complementarity of all-weather roads and the bicycle program. In the absence of treatment, the important underlying assumption of the sub-sample DDD model is that the gender secondary school enrollment gap between Bihar and Jharkhand should evolve in parallel terms for both sub-samples. If the assumption was violated, the split of the DDD estimate by all-weather road connectivity could simply reflect pre-trends, which add up to zero on the aggregate. I test for the parallel trend assumption of the DDD sub-sample split before the treatment in Table 1 using DLHS-2 data. The parallel trend assumption of the DDD estimate for both sub-samples cannot be rejected, increasing the confidence that the sub-sample split of the DDD estimator credibly assesses the heterogeneous impact of the bicycle program by all-weather road connectivity.[14] Motivated by the findings, the triple-difference estimator for each sub-sample takes on the following form:

$$
\begin{aligned}
y_{ihv} = \beta_0 + \beta_1 \cdot T_{ihv} \cdot F_{ihv} \cdot B_{ihv} + \beta_2 \cdot T_{ihv} \cdot F_{ihv} + \beta_3 \cdot T_{ihv} \cdot B_{ihv} \\
+ \beta_4 \cdot F_{ihv} \cdot B_{ihv} + \beta_5 \cdot T_{ihv} + \beta_6 \cdot F_{ihv} + \beta_7 \cdot B_{ihv} + \omega_v + X_{ihv}^{\mathrm{T}} \gamma + \epsilon_{ihv}
\end{aligned}
$$

The dependent variable y_{ihv} corresponds to a dummy for the secondary school enrollment status of individual i in household h and village v, F_{ihv} indicates whether child i is female, T_{ihv} takes on the value 1 if child i is in the post-treatment cohort, and B_{ihv} is a dummy for observation i living in Bihar. X_{ihv}^{T} are household level controls and ω_v village fixed effects. Standard errors are clustered at the village level and observations are weighted using the household sampling weights. The parameter of interest is β_1, which indicates the overall impact of the bicycle program for girls in Bihar, as well as for the sub-samples with and without all-weather roads.

To improve the precision of the estimate and increase the comparability of the villages in the pre- and post-treatment cohorts, as well as the treatment and control states, I include village fixed effects together with a rich set of household level controls.[15] Village fixed effects are particularly useful in this context, as they account for any time-invariant differences across villages which are constant across pre- and post-treatment cohorts. As most village characteristics, such as education and health facilities or banks and post offices take several years to change, the village fixed effects reduce most concerns regarding an omitted variable bias.

One remaining concern is that the sub-sample split picks up the effect of other policies during the treatment period in the state of Bihar, which affect girls differently from boys and differ in their intensity across villages with and without an all-weather road. In particular, improvement in law and order, an increase in public education spending, or the construction of new all-weather roads could bias the estimates. For example, Mukherjee (2012); Aggarwal (2018); Adukia *et al.* (2020) show that the effect of newly

[14]Although I fail to reject the parallel trend test pre-treatment for any specification, the pre-trends are closer to zero conditional on household and village level controls. For this reason, the subsequent analysis focuses on the specification with a rich set of controls. However, the results without controls are qualitatively similar.

[15]Household level controls contain demographic and socioeconomic characteristics. I also report estimates with village level controls instead of village-fixed effects. They include population size, village infrastructure, distance to public transport, and distance to the nearest town.

constructed all-weather roads on school enrollment is more pronounced for girls than boys. Since India started a large rural all-weather road construction program in 2001 (Pradhan Mantri Gram Sadak Yojana (PMGSY)), which connected over 115,000 villages to urban areas until 2015 (Adukia *et al.*, 2020), the triple difference estimates could be inflated by the construction of new all-weather roads.

There are two reasons to believe that concurrent policies, such as PMGSY, are not biasing the estimates. First, Figure A1 in the Appendix shows the number of roads constructed for the treatment and control state from 2001 to 2015 using PMGSY data ([dataset] Adukia *et al.*, 2020).[16] The number of roads constructed during (and before) the treatment period (2006–2008) is comparatively low, as the main wave of road construction only started in 2010, especially in the treatment state of Bihar. This increases the confidence that new all-weather roads are not biasing the estimates. Second, if concurrent policies affect girls differently than boys, they should have a similar impact on enrollment for cohorts just below secondary school. Therefore, Table 2 shows a placebo test of the triple difference estimate for 7th- and 8th-grade enrollment, restricting the age cohorts to live at least 3 km away from middle school and splitting the results by all-weather road connectivity. The effects are insignificant and close to zero across all specifications, increasing the confidence that the empirical strategy is not confounded by concurrent policies, such as the construction of new all-weather roads.[17]

A final concern is that the sub-sample split by all-weather roads reflects a competing mechanism, which highly correlates with villages' connectivity to all-weather roads. Table A6 in the Appendix shows for DLHS-3 that villages in rural areas with an all-weather road are, on average, slightly more developed in terms of village infrastructure and education. Therefore, it might be possible that villages with an all-weather road perceive the value of education for girls to be higher or have less restrictive gender norms compared to villages without an all-weather road. Table A7 investigates this concern with measures for the perceived value of secondary education (9th-grade completion rate) and gender norms (preferred gender of the next child) using data before the treatment (DLHS-2). Both measures do not significantly correlate with the all-weather road dummy for the estimation sample, suggesting that the sub-sample split does not reflect differences in the perceived value of secondary education for girls or gender norms.[18]

[16]The data was retrieved from the additional material of Adukia *et al.* (2020).

[17]Another way to account for the confounding influence of newly constructed all-weather roads would be to use data on villages' connectivity to all-weather roads before the treatment period. Unfortunately, DLHS does not contain information on village names, which prevents me from matching the pre-treatment all-weather road information at the village level.

[18]The estimation sample in this context are girls in Bihar living at least 3 km from secondary school.

Table 2: DDD Estimate - Placebo Test

Dependent variable: Enrolled in or completed grade 7 or 8						
	Overall		All-weather road		No all-weather road	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 8th grade enrollment (13–14-year-olds vs. 15–16-year-olds)						
Treat × female × Bihar	0.001	-0.000	0.025	0.016	-0.010	0.012
	(0.025)	(0.026)	(0.028)	(0.029)	(0.076)	(0.081)
Observations	23699	23722	18366	18389	5333	5333
Panel B: 7th grade enrollment (12–13-year-olds vs. 14–15-year-olds)						
Treat × female × Bihar	-0.029	-0.019	-0.019	-0.011	-0.021	0.015
	(0.023)	(0.023)	(0.025)	(0.025)	(0.066)	(0.071)
Observations	28577	28608	22147	22178	6430	6430
Household level controls	Yes	Yes	Yes	Yes	Yes	Yes
Village level controls	Yes	No	Yes	No	Yes	No
Village fixed effects	No	Yes	No	Yes	No	Yes

Notes: *p<0.1; **p<0.05; ***p<0.01

Triple difference (DDD) placebo estimates for 7th and 8th grade enrollment using DLHS-3 data. The age cutoff is shifted by one year respectively to reflect the expected 7th and 8th grade enrollment age. The household-level controls include indicators for scheduled caste, scheduled tribes, and other backward castes, as well as dummies for Hindus and Muslims. Further controls are household head years of schooling, dummies for household head male, farmer, below the poverty line, TV/radio ownership, and access to electricity. Village-level controls include distance to the bus station, nearest town, railway station, district headquarters, a dummy for middle school, bank, post office, and log of the current village population. Standard errors, clustered at the village level, are in parentheses. Household weights are used to reflect the target population and account for the survey design.

4 Results

4.1 Main Results

Table 3 investigates the triple difference estimate of the bicycle program's impact on secondary school enrollment and the program's complementarity with all-weather roads. Columns 1 and 2 show the positive and statistically significant impact of the bicycle program for girls in Bihar living at least 3 km away (5.4–6.6 percentage points), which was already found by Muralidharan and Prakash (2017). Including village fixed effects in Column 2 slightly reduces the estimate, suggesting that it is important to account for time-invariant village characteristics as they seem to be positively correlated with the treatment cohort in Bihar. Looking at the impact of the program for the sub-sample with (Columns 3 and 4) and without (Columns 5 and 6) all-weather roads, Table 3 indicates sharp differences in the effect of the program. For girls in Bihar who are connected to an all-weather road, the most conservative estimate of the program's impact (including village fixed effects) suggests an increase in the net secondary school enrollment rate of around 6.8 percentage points. Strikingly, there is no positive effect of the program for girls without an all-weather road.[19]

The results in Table 3 add two important aspects towards understanding the bicycle program's effectiveness. First, high-quality road infrastructure matters for the bicycle program's success. Second, the zero impact of the bicycle program for girls without an all-weather road suggests that all-weather roads not only enhance the bicycle program's effect (partial complementarity) but are an important precondition (perfect complementarity).

To ease the interpretation of the findings, I additionally estimate the relative size of the bicycle program's impact for the girls in Bihar living at least 3 km away from school connected to an all-weather road. Adding up the double and single interaction terms, the constant, and the estimated mean impact of the controls, I calculate the subgroup's baseline net secondary school enrollment rate to be 14.6 percent. Hence, the estimated enrollment probability of the average girl in Bihar living at least 3 km away from school connected to an all-weather road would be 14.6 percent *in the absence of the bicycle program*. Using the conservatively estimated 6.8 percentage point impact in Table 3 implies that the offering of bicycles for this subgroup increased the enrollment probability by a notable 46.6 percent (6.8 of 14.6 percentage points). Yet, the average girl in Bihar living at least 3 km away from school without an all-weather road does not experience an increase in the enrollment probability due to the bicycle program, emphasizing the

[19] Testing for the equality of coefficients yields a p-value of 0.08 for the specification with household and village level controls and a p-value of 0.22 for the specification with village fixed effects.

Table 3: DDD Estimate by All-Weather Road Connectivity - Main Results

	Dependent variable: Enrolled in or completed grade 9					
Post-treatment group: Age 14 and 15	Overall		All-weather road		No All-weather road	
Pre-treatment group: Age 16 and 17	(1)	(2)	(3)	(4)	(5)	(6)
Treat × female × Bihar	**0.066****	**0.054***	**0.085*****	**0.068****	**-0.039**	**-0.018**
	(0.030)	(0.028)	(0.033)	(0.032)	(0.062)	(0.063)
Treat × female	0.022	0.035	0.018	0.032	0.094*	0.082
	(0.025)	(0.023)	(0.026)	(0.024)	(0.057)	(0.057)
Treat × Bihar	-0.031*	-0.027	-0.046**	-0.037*	-0.000	-0.013
	(0.019)	(0.019)	(0.021)	(0.021)	(0.043)	(0.044)
Female × Bihar	-0.078***	-0.071***	-0.104***	-0.090***	0.045	0.002
	(0.024)	(0.023)	(0.026)	(0.026)	(0.050)	(0.056)
Treat	-0.128***	-0.131***	-0.128***	-0.132***	-0.128***	-0.123***
	(0.015)	(0.014)	(0.015)	(0.015)	(0.038)	(0.039)
Female	-0.088***	-0.093***	-0.083***	-0.091***	-0.163***	-0.131**
	(0.020)	(0.019)	(0.021)	(0.020)	(0.046)	(0.052)
Bihar	-0.043**	-0.260***	-0.022	-0.245***	-0.071	0.283***
	(0.018)	(0.016)	(0.020)	(0.018)	(0.045)	(0.078)
Constant	0.518***	0.809***	0.504***	0.814***	0.454***	0.311***
	(0.048)	(0.036)	(0.059)	(0.040)	(0.077)	(0.070)
Household level controls	Yes	Yes	Yes	Yes	Yes	Yes
Village level controls	Yes	No	Yes	No	Yes	No
Village fixed effects	No	Yes	No	Yes	No	Yes
Observations	21681	21704	16853	16876	4828	4828
R^2	0.200	0.316	0.197	0.316	0.207	0.305

Notes: *p<0.1; **p<0.05; ***p<0.01

Triple difference (DDD) estimate of the bicycle program's impact on girls' secondary school enrollment by all-weather road connectivity using DLHS-3 data. The household level controls include indicators for scheduled castes, scheduled tribes, and other backward castes, as well as dummies for Hindus and Muslims. Further controls are household head years of schooling, dummies for household head male, farmer, below the poverty line, TV/radio ownership, and access to electricity. Village level controls include distance to the bus station, nearest town, railway station, district headquarters, a dummy for middle school, bank, post office, and log of the current village population. Standard errors, clustered at the village level, are in parentheses. Household weights are used to reflect the target population and account for the survey design.

interdependence of high-quality road infrastructure (all-weather roads) and mode of transport (bicycles) for girls' education choice in India.

The interdependence also becomes apparent when comparing the enrollment probabilities of girls with and without an all-weather road *after the introduction of the bicycle program*. The predicted enrollment probability of the average girl in Bihar living at least 3 km away from school with an all-weather road is 21.4 percent. A similar girl without an all-weather road connection only has a predicted enrollment probability of 17.3 percent. Hence, having a bicycle combined with an all-weather road makes a girl 23.7 percent more likely to enroll in secondary school compared to just having a bicycle.

Next to the relative size of the bicycle program's impact, I can also estimate the program's impact on the gender enrollment gap in secondary school. Repeating the calculation for the average boy in Bihar living at least 3 km away from school connected to an all-weather road yields a net secondary school enrollment rate of 28.6 percent. Hence, the estimated gender enrollment gap for this subgroup *in the absence of the bicycle program* would have been 14 percentage points (14.6 compared to 28.6). Using the 6.8 percentage point impact of the bicycle program yields a reduction of the gender enrollment gap by around 48.5 percent (6.8 of 14 percentage points). The calculation indicates that the bicycle program was able to reach girls who faced large barriers to accessing secondary school relative to boys, almost halving the gender education gap.

4.2 Mechanisms

While the findings suggest that all-weather roads had a crucial role in determining the success of the bicycle program, the mechanisms behind the importance of all-weather roads are still unclear. One reason could be the reduction of distance costs. Muralidharan and Prakash (2017) show that the program's impact follows an inverted U-shape pattern as a function of distance to school. If distance costs are only sufficiently reduced for girls with an all-weather road connection but not without one, they could explain the pattern observed in Table 3. Moreover, if all-weather roads are a precondition of the program's success, then the program's effect for the sub-sample without all-weather roads should not be positive at any distance to secondary school. Table 4 investigates the role of distance to secondary school. Panel A restricts the sample to girls and boys living between 3–10 km away from secondary school (middle distance), and Panel B looks at distances to secondary school of more than 10 km (long distance). The coefficients on the aggregate impact of the program can be seen in Columns 1 and 2. For girls living between 3–10 km away from secondary school, the coefficient with village fixed effects suggests an impact of 6.9 percentage points while the estimate for girls living more than 10 km away is close to zero and insignificant. The findings confirm the inverted U-shape pattern found by Muralidharan and Prakash (2017) and emphasize that distance costs play a crucial role in the program's success.

Table 4: DDD Estimate - Heterogeneity by Distance

Dependent variable: Enrolled in or completed grade 9						
Post-treatment group: Age 14 and 15	Overall		All-weather road		No all-weather road	
Pre-treatment group: Age 16 and 17	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Middle Distance (3–10 km)						
Treat × female × Bihar	0.078**	0.069**	0.096***	0.081**	-0.043	-0.028
	(0.033)	(0.032)	(0.036)	(0.036)	(0.065)	(0.065)
Observations	17984	18007	13883	13906	4101	4101
Panel B: Long Distance (>10 km)						
Treat × female × Bihar	-0.001	-0.015	0.027	0.026	-0.100	-0.098
	(0.069)	(0.069)	(0.083)	(0.083)	(0.129)	(0.133)
Observations	3705	3705	2978	2978	727	727
Household level controls	Yes	Yes	Yes	Yes	Yes	Yes
Village level controls	Yes	No	Yes	No	Yes	No
Village fixed effects	No	Yes	No	Yes	No	Yes

Notes: *p<0.1; **p<0.05; ***p<0.01
Triple difference (DDD) estimate of the bicycle program's impact on girl's secondary school enrollment for middle and long distance using DLHS-3 data. The household level controls include indicators for scheduled castes, scheduled tribes, and other backward castes, as well as dummies for Hindus and Muslims. Further controls are household head years of schooling, dummies for household head male, farmer, below the poverty line, TV/radio ownership, and access to electricity. Village level controls include distance to the bus station, nearest town, railway station, district headquarters, a dummy for middle school, bank, post office, and log of the current village population. Standard errors, clustered at the village level, are in parentheses. Household weights are used to reflect the target population and account for the survey design.

The heterogeneity by distance is similar for the sub-sample of girls with an all-weather road connection. The estimated impact of the program for girls living between 3–10 km away is significant at 8.1 percentage points while I cannot find a statistically significant and positive impact for girls with an all-weather road connection living more than 10 km away. Remarkably, there is no positive effect of the bicycle program at any distance for the sub-sample of girls without an all-weather road.[20]

Consistent with the results in Table 3, the zero effect for the sub-sample without all-weather roads at any distance suggests that all-weather roads are not just enhancing the impact of the bicycle program but are a precondition for the program's success. Moreover, the results confirm that distance costs are

[20]Testing for the equality of coefficients in the middle distance sub-sample yields a p-value of 0.06 (0.14) for the specification with household and village level controls (village fixed effects). For the long-distance sub-sample, the p-values are 0.4 (0.42), respectively.

one important mechanism behind the role of all-weather roads for the bicycle program. Distance costs could only be sufficiently reduced for girls connected to all-weather roads living not too far away from secondary school (3–10 km). Similar to the calculation above, I re-estimate the relative size of the bicycle program's impact for the average girl in Bihar connected to an all-weather road living 3–10 km from school. Using the estimated 8.1 percentage point impact in Table 4, the net secondary school enrollment rate for this subgroup increased by 59.8 percent while the gender education gap reduced by around 51.2 percent, suggesting a large response of those girls to the program.

The results highlight the interdependence of infrastructural elements and are consistent with the O-ring theory by Kremer (1993). Each infrastructural element: road infrastructure (all-weather roads), transportation (bicycles), and schools (distance to school) needs to be adequately provided to shift girls into secondary school. The observation on the interdependence of infrastructural elements also yields an important takeaway for the effectiveness and scalability of infrastructural programs for girls' education. The success of infrastructural programs largely depends on the availability of the other infrastructural elements. Hence, providing bicycles is not enough if schools are not accessible within a 10 km radius and high-quality roads are not provided.

The results in Table 4 also address concerns about the all-weather road sub-sample split reflecting unobserved but highly correlated competing mechanisms, as they would have to be compatible with the distance cost pattern described above. One remaining concern about the findings is the relatively small sample size (727 observations) for the subgroup of girls living more than 10 km away without an all-weather road. The coefficient is imprecisely estimated and might reflect a small-sample bias. To increase the robustness of the results and analyze the sensitivity of the small subgroup, I re-estimate the table including 13-year-olds into the post-treatment group, since around 15 percent of the students enrolled in ninth grade are of age 13 (Muralidharan and Prakash, 2017, p. 340). The results can be seen in Table A8 in the Appendix and are qualitatively similar to the results in Table 4. The increased number of observations for the smallest subgroup brings the estimated coefficient closer to zero. However, the coefficient is still slightly negative and insignificant, suggesting no positive impact of the bicycle program for this subgroup.

While the results in Table 4 establish one underlying mechanism of the importance of all-weather roads for the bicycle program, this does not rule out the existence of other mechanisms. First, differences in parents' and girls' perception of safety might be another explanation behind the pattern in Table 3. Jain and Biswas (2021) show that paved all-weather roads in India have, on average, more street lights and reduce the risk of sexual harassment. As Borker (2021) demonstrates, the perceived risk of street harassment directly impacts the route of travel and college choice of women. In the case of 14 to 15-year-old girls, this might ultimately affect the enrollment decision to secondary school. Second, the combination of all-weather roads and bicycles improves the accessibility of schools throughout the academic year. Since all-weather roads withstand more extreme weather conditions, schools remain accessible during events such as monsoons, increasing the net benefit of enrolling in school. While Idei *et al.* (2020) find no direct effect of all-weather roads on children's school attendance in Cambodia, they find a significant increase in purchases of two-wheeled vehicles (bicycles and motorcycles). Given that the households could afford the investment of two-wheeled vehicles, they also find evidence for a considerable increase in children's school attendance.

Since DLHS-3 is cross-sectional and does not contain information on perceived safety or regular school attendance, I cannot directly test for the importance of these mechanisms. Nevertheless, Table A9 in the Appendix uses the Indian Human Development Survey to descriptively investigate the role of the alternative mechanisms.[21] While I do not find significant differences in the reporting of sexual harassment across Indian households with and without a paved all-weather road, Table A9 confirms the finding by Jain and Biswas (2021) that villages with a paved all-weather road participate more often in public street light programs. Moreover, I find a (marginally) significant negative correlation between paved all-weather roads and girls being frequently absent from secondary school, which is stronger if I restrict the sample to households in possession of a bicycle. Although the evidence is only descriptive, the findings are in line with the literature and suggest that mechanisms beyond the reduction of distance costs might explain the interdependence of all-weather roads and the bicycle program.

5 Robustness

I conduct several robustness checks to analyze the sensitivity and improve the credibility of the results. Table 5 shows results for alternative definitions of the pre- and post-treatment cohort. First, I include 13-year-olds in the post-treatment cohort as some of them entered secondary school. Second, I exclude 17-year-olds from the control group to address concerns regarding a sample selection bias. Girls at the age of 17 might have married and moved to other states instead of enrolling in secondary school, potentially

[21] Although IHDS contains detailed information on measures of regular school attendance and the perception of safety for young women, one drawback is the rather small sample size (15 times smaller than DLHS-3). Therefore, I cannot only rely on the treatment state of Bihar but also need to use the information on all other Indian villages located at least 3 km away from secondary school.

downward biasing the triple-difference estimate (Muralidharan and Prakash, 2017, p. 341). The results are very similar to the main specification in Table 3. For the aggregate specification with village fixed effects, including 13-year-olds yields a positive and significant point estimate of 5.7 percentage points while excluding 17-year-olds increases the estimate to 8.1 percentage points. A similar but slightly stronger pattern emerges for the sub-sample with all-weather roads (7.3 and 11.9 percentage points) while the estimates for the sub-sample without all-weather roads are close to zero and insignificant. Notably, the effect without 17-year-olds is indeed slightly larger, suggesting that the attrition of 17-year-olds downward biases the estimate.

Table 5: DDD Estimate - Alternative Cohort Definitions

Dependent variable: Enrolled in or completed grade 9						
	Overall		All-weather road		No all-weather road	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Post treatment: 13–15-year-olds , Pre-treatment: 16–17-year-olds						
Treat × female × Bihar	0.064**	0.057**	0.086***	0.073**	-0.020	0.000
	(0.026)	(0.025)	(0.029)	(0.028)	(0.058)	(0.060)
Observations	27481	27507	21320	21346	6161	6161
Panel B: Post treatment: 14–15-year-olds , Pre-treatment: 16-year-olds						
Treat × female × Bihar	0.093***	0.081**	0.132***	0.119***	-0.076	-0.073
	(0.035)	(0.034)	(0.039)	(0.038)	(0.078)	(0.077)
Observations	17899	17919	13899	13919	4000	4000
Household level controls	Yes	Yes	Yes	Yes	Yes	Yes
Village level controls	Yes	No	Yes	No	Yes	No
Village fixed effects	No	Yes	No	Yes	No	Yes

Notes: *p<0.1; **p<0.05; ***p<0.01
Triple difference (DDD) estimate of the bicycle program's impact on girls' secondary school enrollment by all-weather road connectivity for various cohort definitions using DLHS-3 data. The household level controls include indicators for scheduled castes, scheduled tribes, and other backward castes, as well as dummies for Hindus and Muslims. Further controls are household head years of schooling, dummies for household head male, farmer, below the poverty line, TV/radio ownership, and access to electricity. Village level controls include distance to the bus station, nearest town, railway station, district headquarters, a dummy for middle school, bank, post office, and log of the current village population. Standard errors, clustered at the village level, are in parentheses. Household weights are used to reflect the target population and account for the survey design.

While the results in Table 5 show the robustness of alternative pre- and post-treatment cohorts, another concern might be that single districts drive the results. To address this concern and improve the comparison of treatment and control state even further, Table A10 in the Appendix restricts the estimation sample to the border districts of Bihar and Jharkhand. Although the drop in the number of observations reduces the statistical power considerably, the pattern of the results is very similar to the main findings. For the sub-sample with an all-weather road connection, there is a positive and significant effect of the bicycle program, while I find no effect for the sub-sample without an all-weather road connection.

6 Conclusion

This paper investigates the complementarity of all-weather roads and a bicycle program in Bihar, which had the goal of empowering female students and reducing the gender education gap in secondary school. Using a triple-difference strategy and splitting the sample by all-weather road connectivity, I find large net secondary school enrollment gains for girls in Bihar living at least 3 km away from secondary school connected to an all-weather road (6.8 percentage points, 46.6 percent). The respective gender education gap for this subgroup reduced by 48.5 percent, suggesting a notable step towards equality of opportunities to access secondary school. Nevertheless, there are no effects of the program for girls without an all-weather road connection, indicating that all-weather roads are not just enhancing the impact of the bicycle program (partial complementarity) but are an important precondition for its success (perfect complementarity).

Exploring the mechanisms behind the importance of all-weather roads for the program, I find that mainly girls with an all-weather road connection living not too close but also not too far away from secondary school drive the results (3–10 km). This suggests that the reduction of distance costs is the main mechanism through which the bicycle program shifts females into secondary school and they could only be sufficiently reduced if girls have access to all-weather roads. I also provide descriptive evidence that lower expected days of absenteeism from secondary school and the improved perception of safety through the provision of street lights might explain the findings.

The results highlight the important and interdependent role of infrastructural elements for the accessibility of secondary schools and emphasize that the O-ring theory by Kremer (1993) also applies to schooling decisions of girls in rural India. Each infrastructural element: road infrastructure (all-weather roads), transportation (bicycles), and schools (distance to school) needs to be adequately provided to shift females into secondary education. While the Right to Education Act (RTE) ensures primary (upper primary) schools to be within a 1 km (3 km) radius of each child, the findings in this paper call for a similar policy intervention for lower secondary schools in India. If bicycles and all-weather roads are provided, the distance to lower secondary schools should not exceed 10 km; otherwise, the distance barrier to school is too large. If the preconditions are fulfilled, bicycle programs might be a cost-effective and scalable alternative to other popular school enrollment policies, such as school construction or conditional cash transfers.

While this paper establishes a clear connection between infrastructural elements and secondary school enrollment in Bihar, further research could investigate the role and complementarity of other infrastructural elements for education choices in low-income settings. Next to bicycles, school buses might serve as an alternative mode of transport for longer distances. Understanding the effectiveness of school buses and their dependence on road infrastructure and distance to school might be another area for future research.

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Appendix

Table A1: Descriptive Statistics for Villages in Bihar and Jharkhand

	Bihar	Jharkhand
Primary school	0.878	0.877
	(0.008)	(0.011)
Distance to nearest primary school (km)	0.617	0.332
	(0.158)	(0.041)
Middle school	0.475	0.522
	(0.012)	(0.016)
Distance to nearest middle school (km)	1.836	1.968
	(0.161)	(0.116)
Secondary school	0.124	0.075
	(0.008)	(0.009)
Distance to nearest secondary school (km)	5.630	7.578
	(0.263)	(0.231)
All-weather Road	0.688	0.947
	(0.011)	(0.007)

Notes: Village level estimates of education facilities and all-weather roads in Bihar and Jharkhand using DLHS-3. Standard errors are clustered at the village level and provided in parentheses.

Table A2: Correlation of Health Facilities and Secondary Schools

Dependent variable: Secondary school in the village		
	(1)	(2)
Health facility in the village	0.169***	0.167***
	(0.015)	(0.015)
Bihar		0.037***
		(0.012)
Constant	0.048***	0.025***
	(0.005)	(0.009)

Notes: *p<0.1; **p<0.05; ***p<0.01
Regression of the availability of a secondary school on the availability of health facilities at the village level. Standard errors are clustered at the village level and provided in parentheses.

Table A3: Descriptive Statistics on Villages with a Secondary School

	Bihar	Jharkhand
All-weather road	0.865	0.971
	(0.024)	(0.020)

Notes: Estimated share of villages in Bihar and Jharkhand with an all-weather road, given they have a secondary school. Standard errors are clustered at the village level and provided in parentheses.

Table A4: DDDD Estimate - Main Results - Alternative Specification

Dependent variable: Enrolled in or completed grade 9						
Post-treatment: Age 14 and 15	At least median dist. (≥3 km)			3–10 km		
Pre-treatment: Age 16 and 17	(1)	(2)	(3)	(4)	(5)	(6)
Treat × female × Bihar × road	0.142	0.118*	0.086	0.152	0.144*	0.112
	(0.091)	(0.069)	(0.074)	(0.117)	(0.078)	(0.079)
Treat × female × Bihar	0.003	-0.033	-0.018	-0.005	-0.048	-0.031
	(0.082)	(0.061)	(0.065)	(0.110)	(0.069)	(0.070)
Household level Controls	No	Yes	Yes	No	Yes	Yes
Village level controls	No	Yes	No	No	Yes	No
Village fixed effects	No	No	Yes	No	No	Yes
R-Squared	0.037	0.201	0.317	0.037	0.201	0.317
Observations	21790	21681	21704	18073	17976	17999

Notes: *p<0.1; **p<0.05; ***p<0.01
Quadruple difference (DDDD) estimate of the bicycle program's impact on girls' secondary school enrollment by all-weather road connectivity using DLHS-3 data. The household level controls include indicators for scheduled castes, scheduled tribes, and other backward castes, as well as dummies for Hindus and Muslims. Further controls are household head years of schooling, dummies for household head male, farmer, below the poverty line, TV/radio ownership, and access to electricity. Village level controls include distance to the bus station, nearest town, railway station, district headquarters, a dummy for middle school, bank, post office, and log of the current village population. Standard errors, clustered at the village level, are in parentheses. Household weights are used to reflect the target population and account for the survey design.

Table A5: Parallel Trend Assumption - Pre-Treatment Test - Alternative Estimates

	Dependent variable: Completed grade 9					
	Whole sample			At least median dist. ($\geq$3 km)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Parallel-trends test for difference-in-difference setting (Bihar)						
Year $\times$ female	0.061***	0.056***	0.063***	0.064***	0.067***	0.077***
	(0.016)	(0.014)	(0.014)	(0.019)	(0.017)	(0.018)
Observations	5407	5407	5407	3096	3096	3096
Panel B: Parallel-trends test for triple-difference setting						
Year $\times$ female $\times$ Bihar	-0.039	-0.045	-0.036	-0.034	-0.026	-0.022
	(0.029)	(0.027)	(0.026)	(0.035)	(0.032)	(0.033)
Observations	7758	7758	7758	4835	4835	4835
Panel C: Parallel-trends test for quadruple-difference setting						
Year $\times$ female $\times$ Bihar $\times$ road	0.026	-0.016	-0.001	0.064	0.024	0.037
	(0.055)	(0.052)	(0.052)	(0.064)	(0.059)	(0.061)
Observations	7758	7758	7758	4835	4835	4835
Household level controls	No	Yes	Yes	No	Yes	Yes
Village level controls	No	Yes	No	No	Yes	No
Village fixed effects	No	No	Yes	No	No	Yes

Notes: *p<0.1; **p<0.05; ***p<0.01

Test for parallel trends pre-treatment using the second phase of DLHS-2 (2004–2005) and alternative specifications. School cohorts are approximated by age groups (15- to 17-year-olds) and the variable year is coded from 0 to 2, taking on the value 2 for the 15-year-old age group (approximate for the school cohort 2003–2004), 1 for the 16-year-old age group (approximate for the school cohort 2002–2003), and 0 for the 17-year-old age group (approximate for the school cohort 2001–2002). The household level controls include indicators for scheduled castes, scheduled tribes, and other backward castes, as well as dummies for Hindus and Muslims. Furthermore, household head years of schooling, a dummy for household head male, and a PCA index for household assets are entailed. Village level controls include distance to the bus station, the nearest town, railway station, district headquarters, middle school, and a dummy for middle school in town. Standard errors, clustered at the village level, are in parentheses. Household weights are used to reflect the target population and account for the survey design.

Table A6: Descriptive Statistics of the Estimation Sample by State and All-Weather Road

	Bihar		Jharkhand	
	All-weather road	No all-weather road	All-weather road	No all-weather road
Female	0.486	0.496	0.476	0.448
	(0.006)	(0.009)	(0.007)	(0.022)
Treat	0.546	0.548	0.589	0.580
	(0.006)	(0.008)	(0.005)	(0.019)
Scheduled caste	0.184	0.191	0.132	0.143
	(0.008)	(0.012)	(0.009)	(0.037)
Scheduled tribe	0.019	0.030	0.380	0.318
	(0.003)	(0.006)	(0.016)	(0.058)
Other backward caste	0.583	0.601	0.409	0.483
	(0.012)	(0.017)	(0.015)	(0.060)
Hindu	0.819	0.828	0.653	0.660
	(0.013)	(0.020)	(0.016)	(0.062)
Muslim	0.177	0.171	0.109	0.106
	(0.013)	(0.020)	(0.011)	(0.047)
Education (Years) Household Head	4.300	3.817	3.899	3.371
	(0.094)	(0.129)	(0.110)	(0.290)
Household Head Male	0.854	0.848	0.952	0.966
	(0.006)	(0.009)	(0.003)	(0.009)
HHold has less than 5 acres of land	0.950	0.948	0.931	0.906
	(0.004)	(0.006)	(0.005)	(0.021)
Below Poverty Line	0.282	0.291	0.404	0.368
	(0.009)	(0.012)	(0.011)	(0.041)
Radio/TV	0.267	0.243	0.303	0.240
	(0.008)	(0.011)	(0.012)	(0.030)
Electricity	0.200	0.121	0.226	0.111
	(0.011)	(0.012)	(0.015)	(0.040)
Middle school	0.527	0.367	0.516	0.359
	(0.021)	(0.030)	(0.023)	(0.081)
Bank in the village	0.086	0.026	0.040	0.005
	(0.012)	(0.011)	(0.009)	(0.005)
Post/telegraph office in the village	0.368	0.243	0.169	0.052
	(0.021)	(0.027)	(0.017)	(0.043)
Log of current pop. in the village	7.988	7.802	6.797	6.723
	(0.048)	(0.080)	(0.044)	(0.130)
Distance to nearest bus station	7.292	9.891	11.742	25.652
	(0.482)	(0.657)	(0.480)	(3.740)
Distance to nearest town	14.075	16.240	16.877	29.880
	(0.561)	(0.849)	(0.600)	(3.901)
Distance to nearest railway station	17.598	18.203	33.652	41.684
	(1.552)	(0.850)	(1.346)	(5.123)
Distance to district headquarter	35.045	33.581	37.610	52.659
	(2.019)	(1.148)	(1.012)	(4.049)

Notes: Mean estimates are restricted to boys and girls in the estimation sample (14- to 17-year-olds) using DLHS-3 data. Standard errors, clustered at the village level, are in parentheses. Household weights are used to reflect the target population and account for the survey design.

Table A7: Correlation of All-Weather Roads and Competing Mechanisms

	Completed 9th grade	Preferred next child: Girl	Preferred next child: Boy
All-weather road	0.022	0.004	-0.017
	(0.020)	(0.007)	(0.018)
Constant	0.104***	0.058***	0.577***
	(0.015)	(0.005)	(0.014)
Observations	1691	5401	5401

Notes: *p<0.1; **p<0.05; ***p<0.01
Correlation of all-weather road connectivity with 9th grade completion rate and gender norm measures using the second phase of DLHS-2 (2004–2005). For 9th grade completion, the sample is restricted to girls in Bihar living at least 3 km away from secondary school. For the gender norm measures, the sample is restricted to women in Bihar living in villages at least 3 km away from secondary school. Standard errors, clustered at the village level, are in parentheses. Household weights are used to reflect the target population and account for the survey design.

Table A8: DDD Estimate - Heterogeneity by Distance including 13-years-olds

Dependent variable: Enrolled in or completed grade 9						
Post-treatment group: Age 13 to 15	Overall		All-weather road		No all-weather road	
Pre-treatment group: Age 16 and 17	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Middle Distance (3–10 km)						
Treat × female × Bihar	0.068*	0.065*	0.091**	0.080**	-0.054	-0.034
	(0.029)	(0.028)	(0.032)	(0.031)	(0.062)	(0.060)
Observations	22813	22839	17581	17607	5232	5232
Panel B: Long Distance (>10 km)						
Treat × female × Bihar	0.017	0.012	0.035	0.041	-0.006	-0.018
	(0.065)	(0.065)	(0.076)	(0.076)	(0.122)	(0.132)
Observations	4677	4677	3748	3748	929	929
Household level controls	Yes	Yes	Yes	Yes	Yes	Yes
Village level controls	Yes	No	Yes	No	Yes	No
Village fixed effects	No	Yes	No	Yes	No	Yes

Notes: *p<0.1; **p<0.05; ***p<0.01
Triple difference (DDD) estimate of the bicycle program's impact on girl's secondary school enrollment for middle and long distance including 13-year-olds using DLHS-3 data. The household level controls include indicators for scheduled caste, scheduled tribes, and other backward castes, as well as dummies for Hindus and Muslims. Further controls are household head years of schooling, dummies for household head male, farmer, below the poverty line, TV/radio ownership, and access to electricity. Village level controls include distance to the bus station, nearest town, railway station, district headquarters, a dummy for middle school, bank, post office, and log of the current village population. Standard errors, clustered at the village level, are in parentheses. Household weights are used to reflect the target population and account for the survey design.

Table A9: Paved All-Weather Roads and Potential Mechanisms

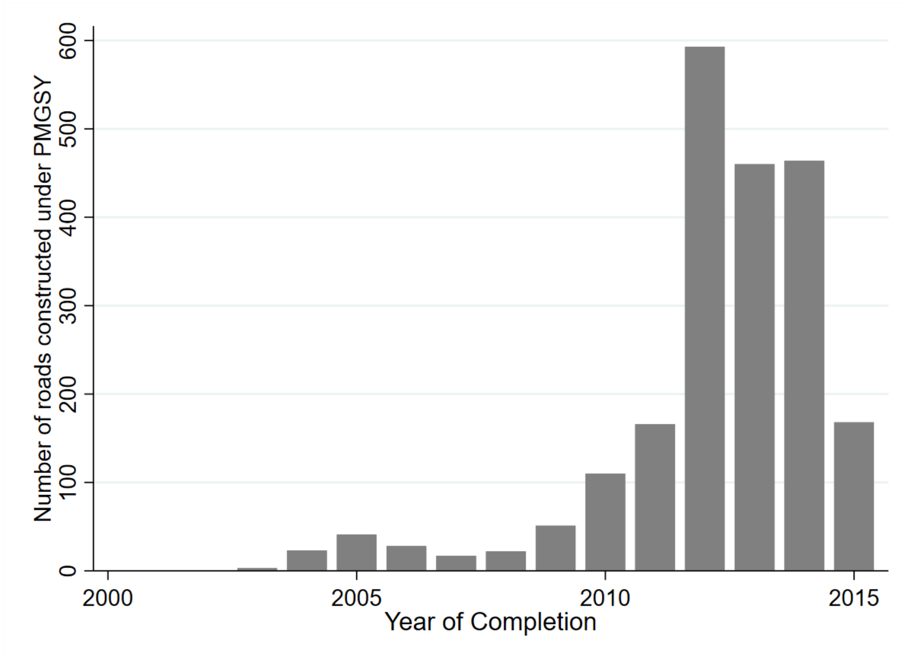
	Frequently absent from secondary school		Sexual harassment	Participation in public
	Whole sample	Bicycles only	of girls	street light program
Paved all-weather road	-0.093*	-0.120*	-0.010	0.091***
	(0.052)	(0.063)	(0.021)	(0.033)
Constant	0.263***	0.255***	0.129***	0.233***
	(0.043)	(0.056)	(0.016)	(0.023)
Observations	858	513	13296	740

Notes: *p<0.1; **p<0.05; ***p<0.01
Correlation of paved all-weather roads with measures of regular school attendance and the perception of safety using IDHS data. Frequently absent from secondary school is coded as 1 if the individual is missing from secondary school at least 7 out of 30 days a month and 0 otherwise. The estimation sample is restricted to all Indian girls currently enrolled in lower secondary school living at least 3 km away from secondary school. Household weights are used to reflect the target population and account for the survey design. Sexual harassment of Girls is coded as 1 if the household respondent reports that sexual harassment of girls in the neighborhood occurs sometimes or often and 0 otherwise. The regression is at the household level for households living at least 3 km away from secondary school. Household weights are used to reflect the target population and account for the survey design. Participation in public street light program corresponds to a dummy indicating whether the village participates in such a program. The regression is at the village level. All specifications cluster standard errors at the village level given in parentheses.

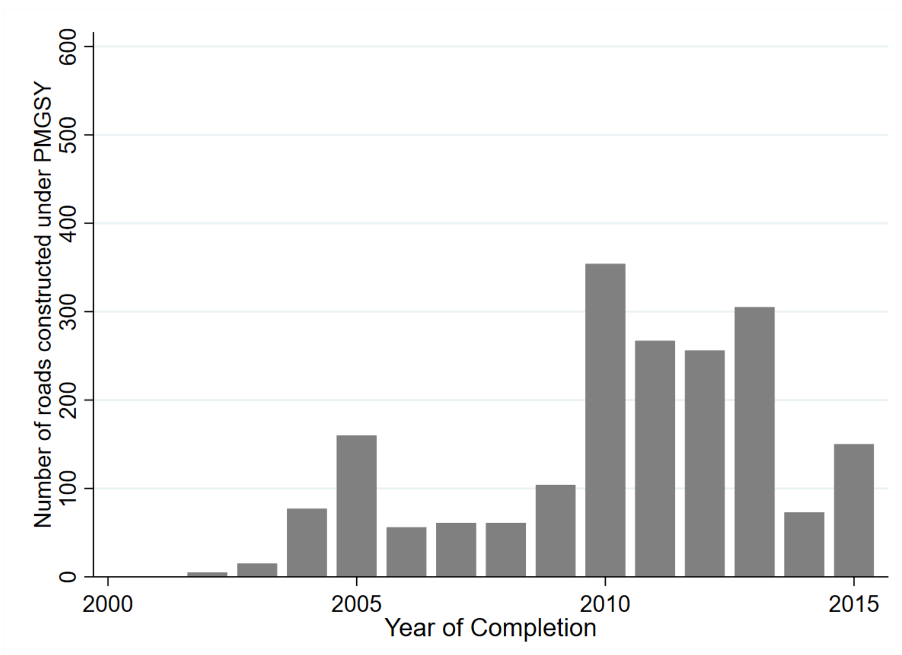
Table A10: DDD Estimate - Border Districts

	Dependent variable: Enrolled in or completed grade 9					
	Overall		All-weather road		No all-weather road	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Post treatment: 14–15-year-olds , Pre treatment: 16–17-year-olds						
Treat × female × Bihar	0.049	0.057	0.078	0.086*	-0.078	-0.066
	(0.041)	(0.042)	(0.047)	(0.049)	(0.076)	(0.079)
Observations	7467	7480	6197	6210	1270	1270
Panel B: Post treatment: 13–15-year-olds , Pre treatment: 16–17-year-olds						
Treat × female × Bihar	0.057	0.073*	0.081*	0.093**	-0.039	-0.019
	(0.039)	(0.039)	(0.044)	(0.046)	(0.072)	(0.075)
Observations	9254	9268	7669	7683	1585	1585
Panel C: Post treatment: 14–15-year-olds , Pre treatment: 16-year-olds						
Treat × female × Bihar	0.086*	0.093*	0.136**	0.139**	-0.143	-0.130
	(0.050)	(0.051)	(0.056)	(0.058)	(0.093)	(0.092)
Observations	6217	6228	5166	5177	1051	1051
Household level controls	Yes	Yes	Yes	Yes	Yes	Yes
Village level controls	Yes	No	Yes	No	Yes	No
Village fixed effects	No	Yes	No	Yes	No	Yes

Notes: *p<0.1; **p<0.05; ***p<0.01
Triple difference (DDD) estimate of the bicycle program's impact on girls' secondary school enrollment by all-weather road connectivity for various treatment and control group definitions restricting the sample to the border districts of Bihar and Jharkhand using DLHS-3 data. The household level controls include indicators for scheduled castes, scheduled tribes, and other backward castes, as well as dummies for Hindus and Muslims. Further controls are household head years of schooling, dummies for household head male, farmer, below the poverty line, TV/radio ownership, and access to electricity. Village level controls include distance to the bus station, nearest town, railway station, district headquarters, a dummy for middle school, bank, post office, and log of the current village population. Standard errors, clustered at the village level, are in parentheses. Household weights are used to reflect the target population and account for the survey design.



(a) Panel A: Bihar



(b) Panel B: Jharkhand

Figure A1: Number of Roads constructed in Bihar and Jharkhand (2001–2015) under PMGSY

Source: Own representation using the additional material of Adukia *et al.* (2020).