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Moritz Seebacher

ifo INSTITUTE
Leibniz Institute for Economic Research
at the University of Munich

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Poschingerstr. 5, 81679 Munich, Germany
Telephone +49(0)89 9224 0, Telefax +49(0)89 985369, email ifo@ifo.de
www.ifo.de

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Infrastructure and Girls' Education: Bicycles, Roads, and the Gender Education Gap in India*

Abstract

How can infrastructure help to reduce the gender education gap in developing countries? In this paper, I analyze the complementarity of all-weather roads and a bicycle program in Bihar, India, which aimed to increase girls' secondary school enrollment rate. Using Indian household survey data combined with a quadruple-difference estimation strategy, I find that the program's main beneficiaries are girls living at least 3km away from secondary schools whose villages are connected with all-weather roads. Their net secondary school enrollment rate increased by over 87 percent, reducing the respective gender education gap by around 45 percent. I find no effect for girls living in villages without an all-weather road, suggesting that all-weather roads are not just complementary to the bicycle program but a precondition for its success. The findings highlight the importance of well-functioning infrastructure for the accessibility of secondary schools and the empowering of girls in India.

JEL Code: 018, I21, I28, H42, J16
Keywords: Roads, bicycles, infrastructure, girls' education, gender education gap, India

Moritz Seebacher
ifo Institute – Leibniz Institute for
Economic Research
at the University of Munich
Poschingerstr. 5
81679 Munich, Germany
seebacher@ifo.de

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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)). Although the gender school enrollment gap reduced over the last decades (see Evans *et al.* (2021)), female students in developing countries still face several barriers to obtaining the same level of educational attainment as male students (see Glewwe *et al.* (2020)). Important barriers, among others, are the distance 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, scalability, and mechanism of education policies that aim to reduce the gender school enrollment gap and the remaining barriers for female students.

In this paper, I analyze the complementarity of all-weather access roads and a bicycle program in Bihar (Mukhyamantri Balika Cycle Yojana), India, which had the goal to improve the secondary school enrollment rate of female students. Although most girls in the estimation sample in Bihar in 2007-2008 had access to primary schools in their villages, only slightly more than 10 percent had direct access to secondary schools.[1] The average distance to secondary school was above 4km, 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)). 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 cash was allocated in public ceremonies, which created social pressure for parents to conform to the program (Muralidharan and Prakash (2017)) and Ghatak *et al.* (2016)) showed that the program was implemented effectively with leakages below 5 percent.[2]

Earlier research indicates that the bicycle program was successful in reducing the gender school enrollment gap in Bihar. Muralidharan and Prakash (2017) use a triple-difference estimation strategy and find that the bicycle program increased the secondary school enrollment rate of girls by 32 percent, implying a reduction of the gender enrollment gap by 40 percent. The effect comes mainly from girls living

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

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

at least 3km (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 role of road infrastructure in the program's success. One important element might have been the connectivity of the rural villages with all-weather roads, which are paved or gravel roads that are functional throughout the year, especially in the rainy season (monsoons), and connect villages to the nearest schools, health centers, and labor markets (Mukherjee (2012)). Considering the human capital decision of girls in Bihar, being connected with an all-weather road in addition to having a bicycle brings several advantages when traveling to school. First, travel time and therefore distance costs to school reduce even further compared to riding a bicycle or walking by foot on dry-season roads or small trails, especially in regions with difficult terrain. Second, 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 or other pathways. Third, the additional reduction of travel time might also improve girls' and parents' perception of safety, which might ease the social constraints and influence the secondary schooling decision of girls.[3] Overall, the combination of all-weather roads and bicycles should increase the net benefits of attending school compared to only obtaining a bicycle.[4]

To examine the heterogeneous impact of the bicycle program by the connectivity of villages to all-weather roads, I use the District Level Household and Facility Survey 3 (DLHS-3) ([dataset] International Institute for Population Sciences (IIPS) (2010)), which is a representative household survey conducted shortly after the start of the bicycle program in Bihar (International Institute for Population Sciences (IIPS) (2010a)). It contains information on the educational attainment of household members and the connectivity of villages to all-weather roads.

To identify the role of all-weather roads, I employ a quadruple-difference estimator where the first three differences correspond to the baseline estimate of the bicycle program's impact, and the last difference tests for the heterogeneity by all-weather roads. Following Muralidharan and Prakash (2017) and Mitra and Moene (2017), I use boys in the state Bihar and boys and girls in the neighboring state Jharkhand as

[3]Borker (2021) shows that safety concerns affect the human capital decision of women and the route of travel they choose to go to college.

[4]While the connectivity of villages to the nearest labor markets theoretically 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 even be a feasible option without a bicycle, especially in light of the restricted mobility of women in India.

natural comparison groups. Exploiting the fact that DLHS-3 was conducted one and a half years after the bicycle program started (2007-2008), I assign 16 to 17-years-old girls (and boys) to the pre-treatment cohort and 14 to 15-years-olds to the post-treatment cohort as 14 to 15-years-olds are expected to have entered ninth grade after the program was implemented.

The main result indicates that girls in the treatment cohort in Bihar who lived at least 3km away from secondary school and whose villages were connected with an all-weather access road experienced an increase in secondary school enrollment by 87 percent, reducing the respective gender education gap by around 45 percent. On the other hand, I find no effect for girls who live at least 3km away and whose villages are not connected with an all-weather access road. In other words, the complete effect of the bicycle program seems to be driven by girls with access to secondary schools by all-weather roads. Hence, all-weather roads are a precondition for the bicycle program's success. The findings emphasize the importance of well-functioning infrastructure for the accessibility of secondary schools and the reduction of the gender education gap in developing countries. The results are also more in line with the O-ring theory by Kremer (1993) than with the idea of sole complementarity: Each infrastructure element (bicycles, all-weather roads, schools) needs to be adequately provided to impact the secondary school enrollment of girls in Bihar.

The paper contributes to the literature on the bicycle program in Bihar (Ghatak *et al.* (2016); Muralidharan and Prakash (2017); Mitra and Moene (2017) by identifying the main beneficiaries in greater detail. Mitra and Moene (2017) find that girls who obtained a bicycle are more likely to complete secondary school, enroll in college, delay childbirth, and marriage, and are less likely to work in agriculture compared to girls who did not benefit from the bicycle program. The result in this paper suggests that the positive long-term effects come from girls who initially lived at least 3km away from secondary school and could rely on well-functioning infrastructure to access school.

The paper also speaks to the extensive literature on school enrollment policies to reduce the gender education gap 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 positively impact 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 reducing the gender education gap if well-functioning infrastructure (schools and high-quality roads) is already provided.

Finally, the paper confirms the positive impact of bicycle programs on girls' educational outcomes found in other low-income settings (see Fiala *et al.* (2022)).

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 and section 5 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 program, which allows for a direct comparison of the school cohorts just before and after the intervention.[6] Next to socioeconomic background characteristics, DLHS-3 contains information about the highest educational attainment (grade) 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 (International Institute for Population Sciences (IIPS) (2010b)), details about the connectivity of villages by an all-weather access road are also documented.

The exact question in the DLHS-3 data is whether the villages are connected by an all-weather road to health facilities.[7] While this does not necessarily imply that villages are also connected to secondary

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

schools by all-weather roads, 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 16 percentage points more likely to have a secondary school compared to villages with no health facility. Second, even if villages with a health facility do not have a secondary school, being connected via an all-weather access road implies that the village is connected to the Indian road network. Therefore, beneficiaries of the bicycle program will still have a direct pathway to school by all-weather roads if villages with secondary schools are also connected to all-weather roads. Using DLHS-3 data, 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 access road, increasing the confidence that a connection to the road network ensures a connection to a secondary school by all-weather roads. Motivated by the findings, I assess the 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.[8]

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 roads and bicycles, I restrict the sample to boys and girls in Bihar and Jharkhand living at least 3km (median distance) away from secondary school. They correspond to the main beneficiaries of the program identified by Muralidharan and Prakash (2017) and roads can only be complementary to bicycles at distances where they are needed to travel to school.

I additionally use the second phase of the prior conducted District Level Health Survey 2[9] (DLHS-2) ([dataset] International Institute for Population Sciences (IIPS) (2006)), to test for parallel trends in the secondary school enrollment rate by gender, state, and all-weather road. One critical advantage of the DLHS-2 data compared to official enrollment data sets[10] is the entailed information about villages' connectivity by all-weather roads, which is necessary to test for pre-trends of the quadruple difference

[8]Notably, the value 0 does not imply that the villages are not connected by roads at all. There could be dry-season roads or small trails. Unfortunately, the DLHS-3 data does not contain information about other road connectivity types, which makes it impossible to investigate the role of different types of roads.

[9]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)).

[10]For example, the District Information System for Education (DISE) data set, which contains official enrollment data.

estimator. Nevertheless, the DLHS-2 data 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 rate and have to define expected school cohorts by age groups to create a pseudo-panel. While this approach faces the drawback that dropout and retention rates need to evolve in parallel terms such that the trends of the ninth-grade completion and ninth-grade enrollment rates are comparable, it can be seen as a first indication of the plausibility of the parallel trend assumption of the quadruple-difference estimator. Nevertheless, the results have to be interpreted with caution and only serve as a first indication.

3 Empirical Strategy

To test for the heterogeneous impact of the bicycle program on secondary school enrollment by the villages' connectivity with an all-weather road, I construct a quadruple difference estimator exploiting the timing of DLHS-3. The expected secondary school entry age (secondary school starts with ninth grade) in India is 14 to 15 years. Since 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-years-old girls as the pre-treatment cohort as they are expected to have entered secondary school before the bicycle program started. The 14 to 15-years-old girls on the other hand should have entered ninth grade after the start of the program in 2006, 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.[11]

Before I present the estimation strategy to test for the heterogeneous impact of the bicycle program, it is important to derive the estimator that credibly identifies the overall impact of the bicycle program. Simply comparing girls' secondary school enrollment rate in Bihar before and after the intervention 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

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

rates were affected in the same way. Using DLHS-2 data, Table 1 shows the difference-in-difference estimator for the ninth-grade completion rate of the age groups from 15 to 17, which roughly represent the ninth-grade school cohorts 2001-2002 to 2003-2004.[12] The results reject the parallel trend assumption and suggest that the respective gender education gap was decreasing in Bihar already 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) and add 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 both states would evolve in parallel terms in the absence of treatment. Adding Jharkhand as a control group might be particularly suitable since the state was part of Bihar before they were divided into two separate states in 2001 (Kingdon (2007)). Table 1 evaluates the plausibility of this assumption in the period before the treatment. Using the 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 also important from an empirical perspective, as it supports the estimation strategy by Muralidharan and Prakash (2017) and Mitra and Moene (2017) 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 likely provides a lower bound of the bicycle program's impact.

While the DDD estimate assesses the overall impact of the bicycle program in Bihar, I can construct a quadruple difference (DDDD) to estimate the heterogeneous impact of the bicycle program by villages' connectivity with an all-weather access road. In the absence of treatment, the important underlying assumption of the DDDD model is that the difference in the gender secondary school enrollment gap between Bihar and Jharkhand should evolve in parallel terms across villages connected and not connected with an all-weather road. If this assumption was violated, the DDDD estimate would be confounded by

[12] 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 (while some already turned 16) where the second phase of the household survey (DLHS-2) took place. Therefore, I assign 15-years-olds to the most recent ninth-grade school cohort 2003-2004, 16-years-olds to the 2002-2003 school cohort, and 17-years-olds to the school cohort 2001-2002. Due to sample selection issues for 17-years-olds, I repeat the estimation only with 15 and 16-years-olds in table A4 the Appendix, yielding similar results.

Table 1: Parallel trend assumption - Pre-treatment test

Dependent variable: Completed grade 9						
	Whole Sample			At least median distance (>=3km)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Parallel-Trends test for Difference-in-Difference setting						
Year × female	0.073***	0.070***	0.072***	0.078***	0.079***	0.080***
	(0.013)	(0.012)	(0.012)	(0.016)	(0.015)	(0.015)
Household level controls	No	Yes	Yes	No	Yes	Yes
Village level controls	No	No	Yes	No	No	Yes
R-Squared	0.047	0.214	0.217	0.046	0.186	0.189
Observations	7758	7758	7758	4835	4835	4835
Panel B: Parallel-Trends test for Triple-Difference setting						
Year × female × Bihar	-0.039	-0.045	-0.045	-0.034	-0.025	-0.026
	(0.029)	(0.028)	(0.027)	(0.035)	(0.033)	(0.033)
Household level controls	No	Yes	Yes	No	Yes	Yes
Village level controls	No	No	Yes	No	No	Yes
R-Squared	0.052	0.215	0.218	0.050	0.188	0.192
Observations	7758	7758	7758	4835	4835	4835
Panel C: Parallel-Trends test for Quadruple-Difference setting						
Year × female × Bihar × road	0.026	-0.021	-0.016	0.064	0.021	0.024
	(0.055)	(0.053)	(0.052)	(0.064)	(0.060)	(0.059)
Household level controls	No	Yes	Yes	No	Yes	Yes
Village level controls	No	No	Yes	No	No	Yes
R-Squared	0.064	0.220	0.222	0.068	0.198	0.200
Observations	7758	7758	7758	4835	4835	4835

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-years-olds) and Year is coded from 0 to 2, taking on the value 2 for the 15-years-old age group (approximate for the school cohort 2003-2004), 1 for the 16-years-old age group (approximate for the school cohort 2002-2003), and 0 for the 17-years-old-group (approximate for the school cohort 2001-2002). The household-level controls include indicators for scheduled caste, 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.

differential trends, yielding biased estimates. I test for the parallel trend assumption of the DDDD estimate before the treatment in Table 1 using DLHS-2 data. The parallel trend assumption of the DDDD estimate cannot be rejected pre-treatment, increasing the confidence that the DDDD estimator credibly assesses the heterogeneous impact of the bicycle program by villages' connectivity with all-weather roads. Motivated by the findings, the quadruple-difference estimator takes on the following form:

$$
\begin{aligned}
y_{ihv} = \beta_0 &+ \boldsymbol{\beta_1} \cdot (\mathbf{T_{ihv}} \cdot \mathbf{F_{ihv}} \cdot \mathbf{B_{ihv}} \cdot \mathbf{R_v}) + \beta_2 \cdot (T_{ihv} \cdot F_{ihv} \cdot R_v) + \beta_3 \cdot (T_{ihv} \cdot F_{ihv} \cdot B_{ihv}) \\
&+ \beta_4 \cdot (F_{ihv} \cdot B_{ihv} \cdot R_v) + \beta_5 \cdot (T_{ihv} \cdot B_{ihv} \cdot R_v) + \beta_6 \cdot (T_{ihv} \cdot F_{ihv}) + \beta_7 \cdot (T_{ihv} \cdot R_v) \\
&+ \beta_8 \cdot (T_{ihv} \cdot B_{ihv}) + \beta_9 \cdot (F_{ihv} \cdot R_v) + \beta_{10} \cdot (F_{ihv} \cdot B_{ihv}) + \beta_{11} \cdot (B_{ihv} \cdot R_v) + \beta_{12} \cdot T_{ihv} \\
&+ \beta_{13} \cdot F_{ihv} + \beta_{14} \cdot B_{ihv} + \beta_{15} \cdot R_v + X_{ihv}^T \gamma + \epsilon_{ihv}
\end{aligned}
$$

The dependent variable y_{ihv} corresponds to a dummy for the secondary school enrollment of child 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, B_{ihv} is a dummy for observation i living in Bihar, and R_v is an indicator for whether village v is connected via an all-weather road. X_{ihv}^T are controls, such as household and village-level characteristics. Standard errors are clustered at the village level and observations are weighted using the household sampling weights in the DLHS-3 data. The parameter of interest is β_1, which indicates the differential impact of the bicycle program for girls in Bihar whose villages are connected with an all-weather road compared to those whose villages are not connected. Next to testing for treatment heterogeneity, it is also important to analyze the marginal effects to assess the actual impact of the program for both subgroups. β_3 shows the marginal effect for girls living without an all-weather road (coefficient of Treat $\times$ female $\times$ Bihar) while $\beta_3 + \beta_1$ refers to the marginal effect for girls living with an all-weather road.

To improve the precision of the estimate and increase the comparability of villages with and without an all-weather road, pre, and post-treatment cohort, and the states Bihar and Jharkhand, I include a rich set of household and village-level controls. Household-level controls contain demographic and socioeconomic characteristics, while village-level controls include population size, access to public facilities, distance to public transport, and distance to the nearest town. The rich set of controls reduces concerns regarding an omitted variable bias and increases the confidence that the quadruple difference estimator assesses the heterogeneous effect of the bicycle program due to villages' connectivity by all-weather roads and

not due to other systematic differences.[13] Nevertheless, the results have to be interpreted with caution as unobservable differences cannot be accounted for.

Another concern is that the road dummy picks up the impact of newly constructed all-weather roads in Bihar after the bicycle program started instead of testing for the complementarity of all-weather roads and the bicycle program. This is a serious concern 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)). Nonetheless, the quadruple difference estimate would only suffer from such a bias if there was a significant difference in the proportion of roads constructed across Bihar and Jharkhand after the bicycle program started. Figure A1 in the Appendix shows the number of roads constructed in Bihar and Jharkhand from 2001 to 2015 using PMGSY data([dataset] Adukia *et al.* (2020)).[14] While Jharkhand constructed slightly more roads than Bihar between 2006 and 2008, the number of roads constructed is quite low as the main wave started in 2010 and the pattern in both states looks very similar. Furthermore, findings by Mukherjee (2012), Aggarwal (2018), and Adukia *et al.* (2020) suggest that the impact of newly constructed all-weather roads on school enrollment is positive for primary school students but decreasing with age[15], resulting in close to zero effects for 14 to 15-years-olds (see Mukherjee (2012); Aggarwal (2018)). Therefore, it is unlikely that the quadruple difference estimate is depicting the impact of newly constructed all-weather roads instead of the complementarity of all-weather roads and the bicycle program.

4 Results

Table 2 shows the quadruple-difference estimate of the heterogeneous impact of the bicycle program on girls' secondary school enrollment by villages' connectivity with an all-weather road. While the preferred estimates include a rich set of village and household-level controls to increase the comparability of villages, states, and treatment and control groups, I also include estimates with no controls to analyze the sensitivity

[13]Table A5 shows descriptive statistics for the estimation sample in Bihar and Jharkhand by villages' connectivity with an all-weather road. There are some systematic differences across states and villages with and without all-weather roads, which need to be accounted for. For example, villages with all-weather roads in Bihar and Jharkhand have more educated household heads and more likely a middle school.

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

[15]Younger children face low opportunity costs and higher returns to education but after middle school, opportunity costs increase due to a potential labor market entry.

of the results. The first three columns show the quadruple difference estimates for girls in Bihar living at least 3km away from secondary school, which are the main beneficiaries identified by Muralidharan and Prakash (2017).

While the estimate with no controls shows a largely positive but insignificant quadruple interaction term, the more precise estimates with controls are marginally significant (at the 10 percent level) and indicate that girls in Bihar who were connected with an all-weather road had an 11.8 percentage point higher increase in (net) secondary school enrollment due to the bicycle program than girls without an all-weather road. Notably, adding controls reduces the estimate on the quadruple-interaction term, suggesting that systematic differences across villages with and without all-weather roads, states, and pre and post-treatment cohorts, would upward bias the differential impact of the bicycle program due to all-weather roads. Calculating the marginal effects by subgroup, row 3 shows that there is no estimated impact of the bicycle program for girls in Bihar who were not connected with an all-weather road[16], while the net secondary school enrollment rate of girls in Bihar connected with all-weather roads increased by 8.5 percentage points (0.118 - 0.033).

This finding adds two important implications to the work by Muralidharan and Prakash (2017). First, the actual main beneficiaries of the bicycle program seem to be girls who were living at least 3km away from secondary school and were connected to an all-weather road. Second, the non-existence of an impact of the bicycle program for girls without an all-weather road suggests that all-weather roads are not just complementary to the bicycle program but an important precondition. This highlights the dependency of the bicycle program's success on well-functioning infrastructure and is more in line with the o-ring theory by Kremer (1993) than with the idea of sole complementarity. Although it is not possible to identify the exact reason why all-weather roads were so important for the bicycle program's success in Bihar, there are several potential explanations. First, they reduce distance costs to school even further compared to driving a bicycle on a dry-season road or trail, which is especially important in difficult terrain. Second, they make schools more accessible throughout the year, especially in seasons with heavy rainfall. Third, lower travel time and easier accessibility might improve the perception of safety for parents and girls, reducing social constraints on girls' mobility.

To assess the effectiveness of the program and identify the main beneficiaries in greater detail, I additionally estimate the relative size of the bicycle program's impact and calculate the baseline net

[16]The estimate is even slightly negative but insignificant.

Table 2: Quadruple Difference (DDDD) Estimate of the Bicycle Program's Impact on Girl's Secondary School Enrollment by All-Weather Roads

Dependent variable: Enrolled in or completed grade 9						
Post-Treatment group: age 14 and 15	At least median Distance (>=3km)			Middle Distance (3-20km)		
Pre-Treatment group: age 16 and 17	(1)	(2)	(3)	(4)	(5)	(6)
Treat × female × Bihar × road	**0.142**	**0.120***	**0.118***	**0.161***	**0.157****	**0.155****
	(0.091)	**(0.069)**	**(0.069)**	**(0.095)**	**(0.071)**	**(0.070)**
Treat × female × road	-0.070	-0.072	-0.072	-0.085	-0.105*	-0.103*
	(0.083)	(0.062)	(0.061)	(0.088)	(0.063)	(0.063)
Treat × female × Bihar	0.003	-0.036	-0.033	-0.006	-0.064	-0.061
	(0.082)	(0.061)	(0.061)	(0.087)	(0.062)	(0.062)
Female × Bihar × road	-0.143**	-0.148***	-0.148***	-0.177***	-0.188***	-0.186***
	(0.061)	(0.055)	(0.055)	(0.064)	(0.057)	(0.056)
Treat × Bihar × road	-0.062	-0.044	-0.042	-0.086	-0.072	-0.069
	(0.053)	(0.048)	(0.048)	(0.056)	(0.050)	(0.050)
Treat × female	0.065	0.091	0.090	0.075	0.117**	0.115**
	(0.077)	(0.056)	(0.056)	(0.081)	(0.056)	(0.056)
Treat × road	0.003	-0.001	-0.002	0.024	0.023	0.021
	(0.046)	(0.041)	(0.041)	(0.049)	(0.043)	(0.043)
Treat × Bihar	-0.010	-0.001	-0.003	0.009	0.023	0.021
	(0.048)	(0.043)	(0.043)	(0.051)	(0.045)	(0.045)
Female × road	0.051	0.078	0.078	0.081	0.112**	0.111**
	(0.054)	(0.049)	(0.048)	(0.057)	(0.051)	(0.050)
Female × Bihar	0.003	0.045	0.044	0.033	0.080	0.078
	(0.053)	(0.049)	(0.048)	(0.056)	(0.050)	(0.050)
Bihar × road	0.051	0.048	0.047	0.085	0.077*	0.074*
	(0.051)	(0.041)	(0.042)	(0.052)	(0.043)	(0.043)
Treat	-0.136***	-0.127***	-0.126***	-0.155***	-0.148***	-0.147***
	(0.042)	(0.038)	(0.038)	(0.045)	(0.040)	(0.040)
Female	-0.123***	-0.162***	-0.162***	-0.149***	-0.192***	-0.191***
	(0.048)	(0.044)	(0.044)	(0.051)	(0.046)	(0.045)
Bihar	-0.002	-0.054	-0.067*	-0.036	-0.083**	-0.092**
	(0.046)	(0.038)	(0.038)	(0.047)	(0.039)	(0.040)
Road	0.069	0.035	0.029	0.036	0.008	0.005
	(0.044)	(0.036)	(0.037)	(0.045)	(0.037)	(0.038)
Constant	0.373***	0.567***	0.490***	0.406***	0.600***	0.525***
	(0.041)	(0.042)	(0.057)	(0.042)	(0.043)	(0.059)
Household level controls	No	Yes	Yes	No	Yes	Yes
Village level controls	No	No	Yes	No	No	Yes
R-Squared	0.037	0.200	0.201	0.037	0.199	0.200
Observations	21790	21704	21681	21001	20918	20895

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

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.

secondary school enrollment rate for this subgroup. Adding up the triple, double, and single interaction terms together with the constant and estimated mean impact of the controls suggests that the baseline net secondary school enrollment rate for the main beneficiaries was 9.6 percent. Repeating the estimation for boys in this subgroup (living at least 3km away and connected with an all-weather road) yields a net secondary school enrollment rate of 28.6 percent. Using the estimated 8.5 percentage point impact in Table 3, this yields an 87.7 percent increase in the net secondary school enrollment rate for the main beneficiaries and a reduction of the gender (net) secondary school enrollment gap by around 45 percent (8.5 of 19 percentage points) in this subgroup. This indicates that the bicycle program was able to reach girls who faced large barriers in terms of secondary school enrollment, almost doubling their net secondary school enrollment rate and halving the respective gender education gap.

While the findings hint at a remarkable impact of the bicycle program for girls living further away from secondary school and being connected with an all-weather road, Muralidharan and Prakash (2017) also showed that the impact of the program follows an inverted U-shape pattern as a function of distance to school. For girls living too far away from secondary school, distance costs and safety concerns might outweigh the benefits of going to secondary school. Motivated by their results, I also estimate the quadruple-difference model for distances between 3 and 20km in columns four to six.[17] The quadruple interaction term is slightly larger compared to the earlier estimates and significant at the 5 percent level, confirming the heterogeneous impact of the bicycle program on village connectivity with an all-weather road. In terms of marginal effects, the DDDD estimate with controls suggests that the bicycle program increased the net secondary school enrollment rate for girls living between 3 and 20 km from secondary school and being connected with an all-weather road by 9.4 percentage points (0.155 - 0.061). This exceeds the earlier estimates and indicates that particularly girls living between 3 and 20 km away from secondary school benefited from the program. Similar to the results presented earlier, there is no impact for girls in middle distance without an all-weather road[18] (see row 3), confirming the necessity of all-weather roads for the bicycle program to be effective.

To increase the robustness and analyze the sensitivity of the results, I use alternative definitions of the pre and post-treatment cohort in table 3. First, I include 13 years-olds in the post-treatment cohort

[17]Using different upper bounds (e.g., 15 km) does not impact the results.

[18]The estimate is slightly negative but not significantly different from zero.

since around 15 percent of the students enrolled in ninth grade are of age 13 (Muralidharan and Prakash (2017, p. 340)). The robustness check is important to get a better understanding of the bicycle program's impact on the total secondary school enrollment as 13 years-olds are also exposed to the bicycle program if they enroll in secondary school. Panel A in table 3 indicates that the findings are similar to the baseline

Table 3: Quadruple Difference (DDDD) Estimate of the Bicycle Program's Impact on Girl's Secondary School Enrollment by All-Weather Roads - Robustness Check

	At least median distance (>=3km)			Middle Distance (3-20km)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Post-Treatment: 13-15-years-olds , Pre-Treatment: 16-17-years-olds						
Treat × female × Bihar × road	0.117	0.102	0.103	0.141*	0.142**	0.142**
	(0.080)	(0.064)	(0.064)	(0.084)	(0.065)	(0.065)
Treat × female × Bihar	0.015	-0.017	-0.017	-0.002	-0.049	-0.049
	(0.072)	(0.057)	(0.057)	(0.076)	(0.058)	(0.058)
Household Level Controls	No	Yes	Yes	No	Yes	Yes
Village level controls	No	No	Yes	No	No	Yes
R-Squared	0.054	0.193	0.194	0.054	0.192	0.193
Observations	27623	27507	27481	26619	26506	26480
Panel B: Post-Treatment: 14-15-years-olds , Pre-Treatment: 16-years-olds						
Treat × female × Bihar × road	0.216**	0.206**	0.203**	0.240**	0.259***	0.256***
	(0.093)	(0.086)	(0.086)	(0.097)	(0.089)	(0.088)
Treat × female × Bihar	-0.035	-0.076	-0.073	-0.048	-0.116	-0.113
	(0.081)	(0.077)	(0.076)	(0.086)	(0.080)	(0.079)
Household level controls	No	Yes	Yes	No	Yes	Yes
Village level controls	No	No	Yes	No	No	Yes
R-Squared	0.025	0.175	0.176	0.025	0.174	0.175
Observations	17990	17919	17899	17311	17243	17223

Notes: *p<0.1; **p<0.05; ***p<0.01
Robustness check of the quadruple difference estimator using alternative pre and post-treatment cohort definitions. 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.

estimates, although the p-value for the quadruple interaction term in the first three columns is slightly above 10 percent. Girls with no all-weather road were not affected by the program (see coefficient of Treat × female × Bihar), while girls living at least 3km away from secondary school with an all-weather road connection largely benefited (8.6 percentage point increase).[19] The effect is even stronger if I exclude

[19]Although the quadruple interaction term is not statistically significant, the marginal effect ($\beta_3 + \beta_1$) for girls with an

girls that live more than 20km away from secondary school (9.3 percentage point increase). Second, I drop 17 years-olds from the control group to address concerns about a potential sample selection bias. Some girls might have married and moved to other states instead of enrolling in secondary school ((Muralidharan and Prakash, 2017, p. 341)). This would lead to a downward bias of the DDDD estimate as the gender secondary school enrollment gap of the control cohort would be understated. Panel B shows that the quadruple interaction term is larger compared to the baseline estimates and highly significant (at the 1 percent level), confirming that the baseline estimates are more likely to be a lower bound. Also in this specification, there is no evidence that girls without an all-weather road benefited from the program, while the estimated impact of the bicycle program for girls with an all-weather road that lived at least 3km away increases to remarkable 13 percentage points (0.203-0.073).

5 Conclusion

To conclude, this paper investigated the complementarity of all-weather roads and a bicycle program in Bihar, which intended to reduce the gender education gap in secondary school. Using a quadruple difference estimator and DLHS-3 data, I find large net secondary school enrollment gains for girls in Bihar living at least 3km away from secondary school and being connected with an all-weather road (8.5 percentage points, 87.7 percent), while no impact can be found for girls with no all-weather road. The results indicate that all-weather roads are not just complementary to the bicycle program but a precondition for the program's success, highlighting the importance of well-functioning infrastructure for the accessibility of secondary schools and the empowerment of girls in India.

To improve the external validity of the findings, further research could assess the impact and mechanism of bicycle programs in other Indian states, which followed Bihar's education policy. Furthermore, the role of difficult terrain, the quality of all-weather roads, and perceived safety could be analyzed to understand the mechanism of the bicycle program in greater detail.

all-weather road living at least 3 km away from secondary school is significant at the 5 percent level.

Appendix

Table A1: Descriptive Statistics for Estimation Sample in Bihar and Jharkhand

	Bihar	Jharkhand
Primary school	0.901	0.875
	(0.008)	(0.017)
Distance to nearest primary school	0.432	0.300
	(0.133)	(0.050)
Middle school	0.527	0.537
	(0.014)	(0.021)
Distance to nearest middle school	1.485	1.729
	(0.126)	(0.115)
Secondary school	0.138	0.075
	(0.010)	(0.010)
Distance to nearest secondary school	4.413	7.300
	(0.126)	(0.255)
All-weather Road	0.710	0.956
	(0.013)	(0.007)

Notes: Mean estimates are restricted to boys and girls in the estimation sample (14 to 17-years-olds). 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 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.

Table A3: Secondary Schools and All-Weather Roads

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

Notes: Estimates are restricted to villages with a secondary school. Table A3 shows the fraction of villages with an all-weather road.

Table A4: Parallel trend assumption - Pre-treatment test - Robustness Check

Dependent variable: Completed grade 9						
	Whole Sample			At least median distance (>=3km)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Parallel-Trends test for Difference-in-Difference setting						
Year × female	0.102***	0.091***	0.090***	0.106***	0.101***	0.097***
	(0.021)	(0.020)	(0.020)	(0.026)	(0.024)	(0.025)
Household level controls	No	Yes	Yes	No	Yes	Yes
Village level controls	No	No	Yes	No	No	Yes
R-Squared	0.037	0.185	0.187	0.035	0.161	0.164
Observations	5970	5970	5970	3747	3747	3747
Panel B: Parallel-Trends test for Triple-Difference setting						
Year × female × Bihar	-0.032	-0.031	-0.026	-0.038	-0.021	-0.015
	(0.049)	(0.046)	(0.046)	(0.058)	(0.055)	(0.055)
Household level controls	No	Yes	Yes	No	Yes	Yes
Village level controls	No	No	Yes	No	No	Yes
R-Squared	0.044	0.187	0.189	0.042	0.164	0.167
Observations	5970	5970	5970	3747	3747	3747
Panel C: Parallel-Trends test for Quadruple-Difference setting						
Year × female × Bihar × road	-0.108	-0.116	-0.110	-0.080	-0.101	-0.093
	(0.085)	(0.084)	(0.083)	(0.096)	(0.095)	(0.094)
Household level controls	No	Yes	Yes	No	Yes	Yes
Village level controls	No	No	Yes	No	No	Yes
R-Squared	0.055	0.192	0.193	0.058	0.174	0.175
Observations	5970	5970	5970	3747	3747	3747

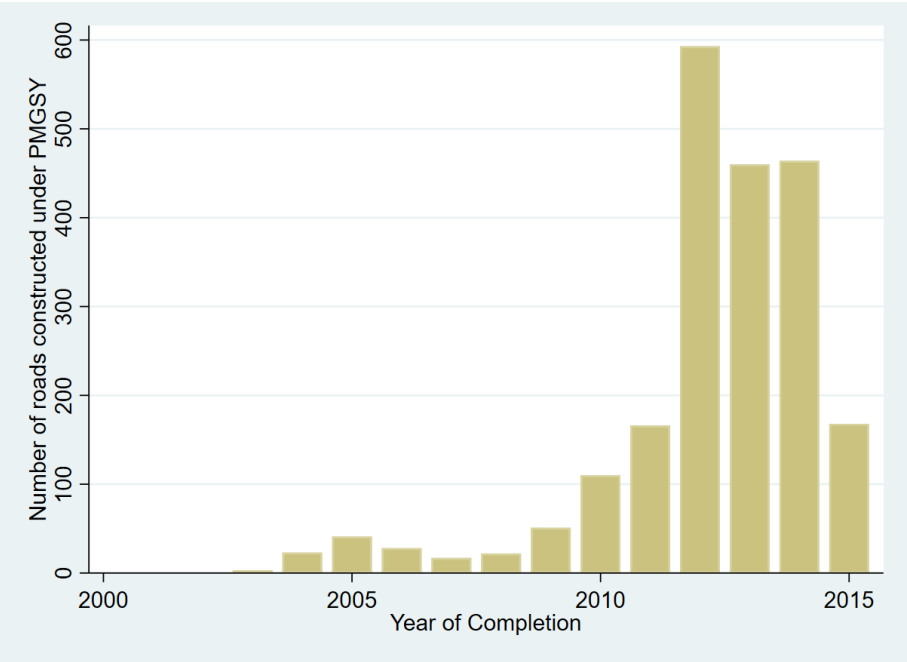
Notes: *p<0.1; **p<0.05; ***p<0.01

Test for parallel trends pre-treatment using the second phase of DLHS-2 (2004-2005) and excluding 17-years-olds as a robustness check. School cohorts are approximated by age groups (15 to 16-years-olds) and Year is coded as a dummy, taking on the value 1 for the 15-years-old age group (approximates for the school cohort 2003-2004) and 0 for the 16-years-old-group (approximates for the school cohort 2002-2003). The household level controls include indicators for scheduled caste, scheduled tribes, and other backward castes, as well as dummies for Hindus and Muslims. Furthermore, household head years of schooling, dummies 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.

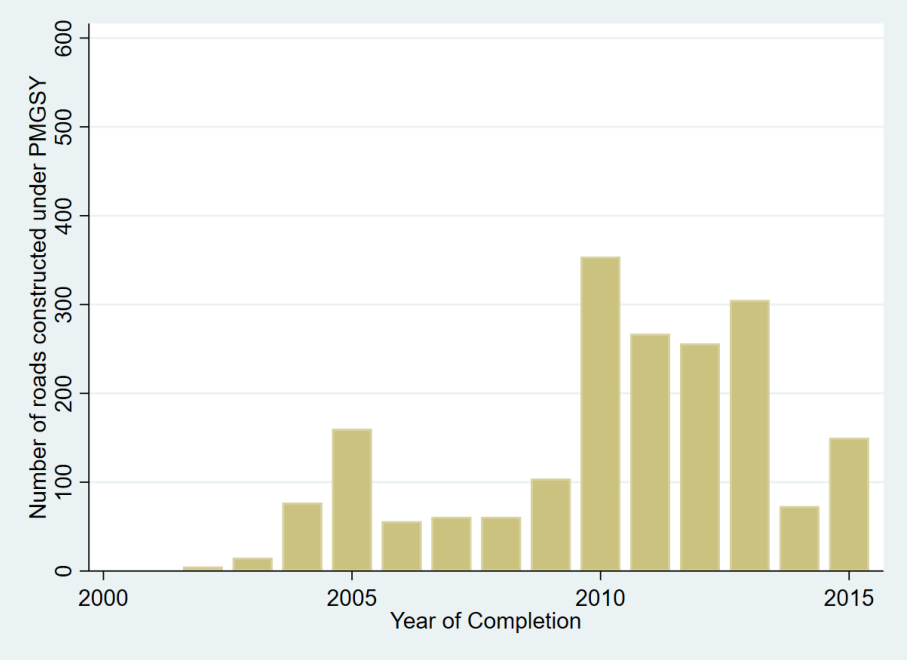
Table A5: Descriptive Statistics of Estimation Sample by State and All-Weather Road

	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)	(0.015)	(0.057)
Other backward caste	0.583	0.601	0.409	0.483
	(0.012)	(0.016)	(0.014)	(0.060)
Hindu	0.819	0.828	0.653	0.660
	(0.013)	(0.019)	(0.015)	(0.062)
Muslim	0.177	0.171	0.109	0.106
	(0.013)	(0.019)	(0.011)	(0.047)
Education (Years) Household Head	4.300	3.817	3.899	3.371
	(0.091)	(0.127)	(0.107)	(0.290)
Household Head Male	0.854	0.848	0.952	0.966
	(0.006)	(0.009)	(0.003)	(0.009)
Household 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
	(0.008)	(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)	(0.014)	(0.040)
Middle school	0.527	0.367	0.516	0.359
	(0.021)	(0.029)	(0.023)	(0.080)
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
	(0.045)	(0.078)	(0.043)	(0.127)
Distance to nearest bus station	7.292	9.891	11.742	25.652
	(0.480)	(0.653)	(0.475)	(3.701)
Distance to nearest town	14.075	16.240	16.877	29.880
	(0.550)	(0.834)	(0.593)	(3.867)
Distance to nearest railway station	17.598	18.203	33.652	41.684
	(1.546)	(0.840)	(1.193)	(5.113)
Distance to district headquarter	35.045	33.581	37.610	52.659
	(2.008)	(1.121)	(0.985)	(4.054)

Notes: Mean estimates are restricted to boys and girls in the estimation sample (14 to 17-years-olds). 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).

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