Road to the Future: Identifying Impacts of Roads on Education in Colombia

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Abstract

This study examines the impact of Colombia's Public-Private Partnership (PPP) road concessions on educational outcomes using a staggered difference-in-differences approach with student-level data (2006-2021). I find that road project completion leads to statistically significant increases of 0.169 standard deviations in math and 0.11 standard deviations reading literacy scores. Furthermore, child labor decreases by 3%, while higher education pursuit increases by 4.8%. These robust results suggest PPP-driven road investments effectively promote human capital development, urging policymakers to consider these short- and long-term educational effects when evaluating infrastructure.

JEL Codes: I21, I25, O18, R42

Keywords: Road Infrastructure, Education, Economic Development, Public-Private Partnerships (PPPs), Developing Countries, Human Capital

1 Introduction

Access to quality education is a fundamental right, yet for millions of children in Colombia, the journey to school is fraught with challenges such as traversing miles of rugged terrain, crossing treacherous rivers on makeshift bridges, or braving perilous weather conditions, all for the chance to learn. In 2013 the Student Enrollment System in Colombia reported that this was the reality for around 2.9 million students. Pointing to the fact that inadequate road infrastructure, particularly in rural areas, poses a significant barrier to educational attainment, hindering economic mobility and perpetuating inequality.

The inadequacy of road infrastructure is a particularly pressing issue in developing countries, where limited access often coincides with severe educational disparities. Evidence suggests a strong correlation between road accessibility and educational outcomes. For instance, comparing the rural access index (RAI) (Ahmed et al., 2016) with PISA 2018 results (Organisation for Economic Co-operation and Development, 2019) reveals that countries with better road access tend to achieve higher scores in math and language (See Figure 10). Specifically, a 15% increase in RAI translates into an improvement of 22 points in language and 25 points in math on the PISA test—equivalent to more than a year of school learning (Organisation for Economic Co-operation and Development, 2021).

This study investigates the impact of Colombia's road concession program on education, focusing on student performance in math and reading literacy as measured by the SABER 11 standardized test. This program, designed to leverage private capital to improve the National Road Network (NRN) due to the state's limited resources, offers a unique opportunity to examine the effectiveness of Public-Private Partnerships (PPPs) in promoting educational outcomes. Given the ongoing debate surrounding the impact of road development on education, this study aims to answer the following research question: Does the implementation of PPP-driven road concessions in Colombia lead to improved educational outcomes, as measured by performance on the SABER 11 standardized test?

While adequate road infrastructure is widely recognized as crucial for economic growth and development (Allen & Arkolakis, 2022; Donaldson, 2019; Fajgelbaum, 2020), the impact of road development on education remains subject to debate. Some studies have shown that improved road networks can increase access to education, reduce travel time, and potentially increase attendance (Adukia, Asher, & Novosad, 2020; Asher & Novosad, 2020; Mukherjee, 2012), while others highlight potential downsides, such as increased economic activity drawing children into the labor force and reducing their time for education (Fafchamps & Wahba, 2006a). This underscores the need for rigorous analysis to understand the complex interplay between roads and educational outcomes, particularly within the context of PPP-driven infrastructure projects like Colombia's road concession program.

PPPs in infrastructure development are increasingly common in Colombia (Casady & Parra, 2021; Tye, 2013), but their impact on education remains understudied. Unlike publicly funded programs, PPPs may prioritize economically profitable routes, potentially bypassing areas with greater educational needs. Moreover, the quality, maintenance, and long-term sustainability of PPP infrastructure might differ from publicly funded projects, leading to varied effects on education over time. Colombia provides a particularly relevant context for this investigation. Despite recognizing education as a fundamental right and public service, the country faces persistent disparities in educational access and quality, especially in rural areas where 22% of the population lacks access to all-weather roads (Ahmed et al., 2016). Furthermore, previous research suggests that road development in Colombia has unequally impacted production and income distribution (Quintero & Sinisterra, P2022), raising concerns that road concessions might exacerbate existing inequalities.

By focusing on this program, this study makes three key contributions to the literature. First, it makes a novel contribution by directly examining the impact of road concession programs on student academic performance, specifically focusing on the long-term benefits for human capital development. Addressing a significant gap in existing research, which is mainly focused on publicly funded programs Adukia et al. (2020), this study provides critical information on how road concession programs can effectively leverage infrastructure investments to improve educational outcomes. Moreover, by demonstrating the tangible improvements in student math scores and higher education pursuit following road improvements, this research establishes roads as a crucial means for fostering human capital development within communities served by PPP concessions.

Second, while previous studies have examined the impact of increased income on families and child labor (Fafchamps & Wahba, 2006a), this study investigates the dynamic of road improvements on child labor participation, offering insights into the potentially complex relationship between infrastructure development and child labor dynamics in all the process of construction.

Third, this study employs a difference-in-differences approach with staggered treatment to address the methodological challenge of evaluating infrastructure projects with continuous and evolving impacts. Unlike traditional DiD methods (Callaway & Sant'Anna, 2021; Goodman-Bacon, 2021; Roth, Sant'Anna, Bilinski, & Poe, 2023), this study recognizes that road construction unfolds gradually, with impacts potentially arising even before the project is fully completed. This study leverages this gradual rollout to its advantage, examining how educational outcomes change at various stages of construction (10%, 50%, and 100% completion). This allows for a more refined causal assessment, capturing how the effects on education dynamically unfold as the road progresses through different stages of development.

This study leverages data from 155 schools annually over a 16-year period (2006-2021), representing approximately 9,500 students per year. The student population exhibits some age variability, with the youngest 10% being under 16 years old and the oldest 10% being over 19. Slightly more than half the students (54%) were women. The schools are located across 92 municipalities, with an average of 66 schools per year participating in the treatment group and 89 in the control group.

This study provides compelling evidence that Colombia's road concession program has yielded positive and significant impacts on educational outcomes. Employing a dynamic difference-in-differences approach, I find that students attending schools near roads improved through the concession program experience an increase of 0.16 standard deviations in math scores and 0.11 standard deviations in reading literacy scores. This improvement is evident across various stages of road construction, demonstrating the program's dynamic and evolving influence on education. Moreover, my analysis reveals a 3% reduction in child labor participation and a 4.8% increase in the proportion of students pursuing higher education following road improvements. These findings underscore the transformative potential of road infrastructure, particularly through public-private partnerships, to enhance educational opportunities and promote human capital development in developing countries.

The findings of this study hold important implications for policymakers considering PPPs as a mechanism for promoting human capital development. The evidence suggests that well-designed road concession programs, particularly those that prioritize connectivity for under-served rural communities, can contribute to significant and lasting improvements in educational outcomes.

The remainder of this article is organized as follows. Section 2 presents the institutional context related to political regulations, roads, concession agreements, and education in Colombia. Section 3 describes the data used in this study. The empirical strategy, which allows for the estimation of causal inference, and the mechanism by which roads can affect education, is presented in Sections 4 and 5, respectively. The results are discussed in Section 6, and the article concludes in Section 7. The tests and additional results are reported in the Appendix.

2 Education and Road Infrastructure in Colombia

Access to quality education is fundamental for social and economic development in Colombia. It is enshrined in the Colombian constitution as a fundamental right and public service (Government of Colombia, 1991). A substantial portion of Colombian students, between 23.8% and 18.6% from elementary to secondary levels, attend rural schools (LEE, 2023), highlighting the importance of ensuring equitable access in these areas. However, long-standing challenges persist, with inadequate road infrastructure posing a significant barrier to educational opportunities and hindering social mobility.

This analysis uses data from 2006 to 2019, drawing primarily on two key sources. First, I use student-level scores from the SABER 11 standardized test, a national assessment of academic achievement in Colombia. Second, I incorporate georeferenced data on road construction projects across the country, including details on project timelines and completion status. By linking these datasets at the school level, I am able to examine the educational outcomes of schools located near road construction projects before and after these roads have been intervened, accounting for the staggered nature of project implementation.

In Colombia, many schools and communities are isolated due to the lack of adequate road infrastructure. My analysis reveals that 50% of the schools are more than 1 kilometer from a road with 24/7 vehicular access, with 24% located more than 5 km away (Figure 7)). Moreover, the Rural Access Index (RAI), a key indicator measuring the proportion of rural population with access to an all-weather road within a reasonable distance of 2 kilometers, provides a broader context. The RAI in Colombia stands at 78% (Ahmed et al., 2016), indicating that 22% of the rural population lacks the aforementioned access. This figure, while better than the RAI for Africa (66%), lags behind the United States (14%) and the Latin American and Caribbean average (41%), underscoring the need for continued infrastructure improvements in Colombia.

The impact of road infrastructure on educational outcomes has been widely documented in the literature. For example, Adukia et al. (2020) found that road improvements in India significantly increased school enrollment and reduced student absenteeism by lowering transportation costs. Similarly, K. Idei, Kato, and Morikawa (2020) examined rural road improvements in Cambodia and showed that better connectivity led to higher school attendance rates. These findings suggest that road accessibility plays a crucial role in reducing barriers to education, particularly in remote areas. However, improvements in road infrastructure do not always translate directly into better educational outcomes. Several factors may moderate the effect. For instance, while roads reduce travel time, they may also increase access to informal labor markets, potentially pulling students away from school, as documented by Fafchamps and Wahba (2006b).

To address these infrastructure gaps and foster development, the Colombian government has increasingly turned to public-private partnerships (PPPs), notably through road concession programs. Historically, the road network, particularly in rural areas, suffered from chronic underfunding, hampering economic growth, social inclusion, and, crucially, educational opportunities. Security concerns in certain regions further compounded this problem. While PPPs offer a potential solution by leveraging private capital, it's crucial to acknowledge the inherent trade-off between private financial incentives and broader public interest goals. Recognizing the urgent need for improved infrastructure but facing limited state resources, PPPs offered a promising alternative. Law 80 of 1993 and Law 105 of 1993 laid the legal groundwork for road concessions, marking a turning point by enabling private sector participation in financing, building, operating, and maintaining vital road segments.

A key concern with PPP road concessions is the potential for route selection bias. Private companies, motivated by profit, may prioritize routes that maximize revenue generation (connecting major commercial centers, minimizing construction costs), potentially neglecting areas with the greatest educational needs or those requiring more challenging and expensive infrastructure investments. This can lead to situations where marginalized rural communities are bypassed, thereby limiting the positive impact of road improvements on their educational outcomes. However, the public sector ultimately selects the company and proposal for road construction, which constrains profit-driven bias. To remain competitive, companies must present proposals that balance economic feasibility with social welfare considerations, including educational outcomes.

The Build-Operate-Maintain-Transfer model, where private companies are granted concessions to recover costs through tolls, became the cornerstone of this program. Since its inception in the 1990s, the road concession program has evolved through five generations, with each generation focusing on addressing specific challenges and priorities. The third and fourth generations, commencing in the 2010s and central to this study, marked a shift towards developing integrated "corridors of commerce" prioritizing trade, regional integration, and socio-economic development, making it particularly relevant for understanding the impact of road concessions on education.

A typical road concession project in Colombia unfolds through several key stages, as illustrated in Figure 1. Following the contract signing, an initial period of approximately six months, known as "Stage Zero", is dedicated to preparatory work before pre-construction begins, culminating in the signing of the initiation document. The subsequent Pre-Construction stage, typically lasting 18 to 24 months, encompasses crucial studies such as initial feasibility assessments, route selection, and environmental impact evaluations. Once these groundwork steps are completed, the Construction stage commences, encompassing all activities related to building the road and associated infrastructure. This phase generally requires an average of 10 years to complete.

It's important to distinguish between the construction phase, which can be lengthy, and the period after the road is completed and operational. While the construction period might bring temporary disruptions, this study's primary focus is on the long-term and sustained impacts on educational outcomes that emerge once the road is fully functional. I specifically define "short-term" as the time during construction in comparison with the "long-term" effect, which are the effects after construction. The concessionaire assumes responsibility for road maintenance and toll collection, often lasting 25 to 30 years (Sanchez (2022)).

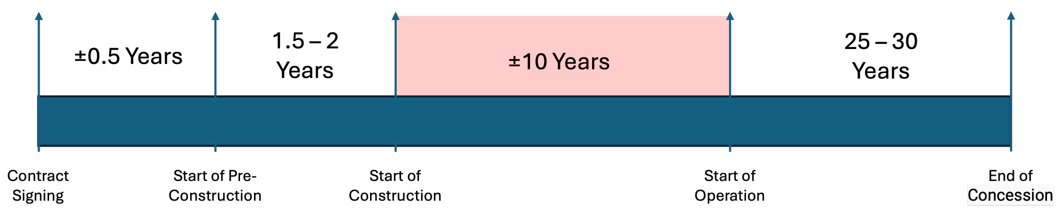


Figure 1: Typical Stages of a PPP Road Concession Project in Colombia.

3 Data

This study investigates the causal impact of improved road infrastructure on academic performance in Colombia. I leverage a rich dataset spanning 2006 to 2019, encompassing student-level academic records, school characteristics, and detailed information on road construction projects. My analysis centers on the role of improved road accessibility in enhancing educational outcomes, particularly in regions historically hindered by poor transportation infrastructure.

My analysis focuses on students attending schools located within a 1500-meter radius of a road construction or improvement project. This distance, equivalent to a 15-20 minute walk, is informed by the Rural Access Index (Ahmed et al., 2016) but tailored to the Colombian context. Due to local geographical conditions, a 1.5 km Euclidean distance reliably captures a reasonable walking distance (representing approximately 72% of the actual distance) and allows me to isolate the localized impact of improved road access on school accessibility and, subsequently, academic performance.

Road Infrastructure Data

I utilize data on road construction and their progress from the INVIAS georeferenced vector database of roads in Colombia and National Public Procurement Agency (Instituto Nacional de Vías (INVIAS) (2024), Table 15). This detailed database provides critical information on the start and completion dates of road projects, enabling me to track the timing of road access for each school in my sample. By linking this temporal dimension to student-level academic data, I can employ a difference-in-differences approach to estimate the causal impact of road improvements on educational outcomes over time.

My analysis focuses on national roads under concession contracts, as these projects typically involve substantial investments in upgrading and expanding existing road networks, leading to more significant potential impacts on accessibility. To characterize these road infrastructure projects and their influence on school accessibility. I pinpointed the commencement of construction for each project using the project start date, establishing a clear timeline for possible accessibility improvements. The project completion date then allows me to pinpoint when a road project reached 100% completion, marking the full realization of its intended accessibility benefits.

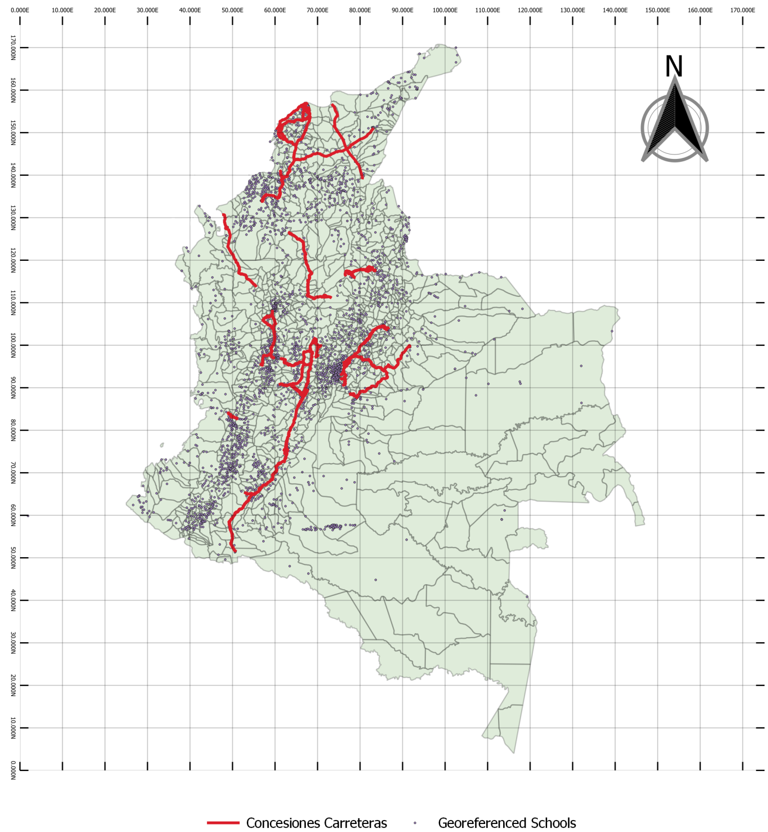


Figure 2: Roads under concession and schools georeferenced. Purple points illustrate the Georeferenced schools, and the red lines illustrate the roads under concession at the considered time.

Construction Progress and Gradual Impact:

I recognize that the impact of road infrastructure on school accessibility is not instantaneous or simply a matter of whether a road exists or not. The construction process itself can span several years, and accessibility benefits may accrue gradually as different phases of a project are completed. To mitigate potential temporal misalignment bias, I utilize data on construction progress milestones (10%, 50%, 100%) to create time-varying measures of road accessibility. This approach allows us to capture the evolving impact of road improvements throughout the construction period, providing a more accurate representation of the relationship between infrastructure development and educational results (See Table 1).

Table 1: Time Required for Road Construction Progress (Years)

Construction Phase	**0%-10%**	**10%-100%**	**0%-50%**	**50%-100%**	**0%-100%**
Mean	4.2	9.0	5.8	3.2	12.3
Median	4	8.5	5	3	12.5
Standard Deviation	1.9	3.1	3.0	2.5	6.4
Number of Road Projects	13	10	12	9	8

Note: This table shows the time (in years) taken for different phases of road construction progress, based on available project data. Each phase represents the duration from the starting point (project signing or start of physical construction as appropriate for the phase definition) to the specified completion percentage. For example, "0%-50%" indicates the average time from project signing to reaching 50% completion. The "Number of Road Projects" reported for each phase varies because clear and consistent data on the duration for each specific phase (e.g., 0%-10%, 10%-100%) was not uniformly available across all road concession projects in the master list (Appendix Table 15). This table therefore presents descriptive statistics for the subset of projects for which these specific phase durations could be reliably calculated. This table is for descriptive purposes regarding typical construction timelines and is distinct from the sample of schools/students used in the main DiD estimations, which includes all schools near any project that reached the relevant milestone during the study period.

Standarized Math and Reading Literacy Score:

To facilitate comparisons across years and account for potential changes in exam difficulty, I standardize the raw SABER 11 Mathematics and Reading Literacy scores. This standardization involves centering the scores using the national mean and scaling them by the national standard deviation for each year. This transformation yields standardized scores with a mean of 0 and a standard deviation of 1, allowing for straightforward interpretation of student performance relative to the national average. A standardized score of 0 indicates that a student achieved the national average for that year, while scores above or below 0 reflect performance above or below the national average, respectively.

To address the potential for confounding and isolate the causal effect of road infrastructure, I employ a staggered difference-in-differences (S DiD) approach. This method leverages the variation in the timing of road project completion across different schools, allowing me to compare changes in academic outcomes for schools before and after they gain access to improved roads. By exploiting this temporal variation, I can control for time-varying confounders and reduce my reliance on a perfectly matched control group, strengthening the causal interpretation of my findings.

INSE: Socioeconomic Status Index

The INSE (Índice de Nivel Socioeconómico, or Socioeconomic Status Index) is a school-level measure constructed by ICFES (Instituto Colombiano para la Evaluación de la Educación) to capture the socioeconomic background of students taking the SABER 11 exam. It serves as a proxy for the economic resources, parental education, and access to services available to students at each school. Higher INSE values indicate a greater degree of socioeconomic advantage. Since 2012, ICFES has employed Item Response Theory (TRI, or Item Response Theory) to calculate the INSE. The TRI approach allows in probabilistic terms the relationship that exist between a group of items and a variable which not can observe directly, such as INSE. The model incorporates several dimensions: parental education, parental occupation and household wealth (measured through the consumption of goods and access to services). A Principal Component Analysis (PCA) is performed to reduce the dimensions and to validate its unidimensionality.

Child Labor Index:

To assess the prevalence of child labor within our sample, I construct a school-level Child Labor Index. This index leverages self-reported data from the SABER 11 survey, which includes questions about students' participation in the labor force. Specifically, I calculate the proportion of students in each school s and year t who report being engaged in any form of paid work. This ratio, ranging from 0 to 1, provides a measure of child labor intensity within each school. A higher value indicates a greater proportion of students engaged in work, potentially reflecting economic hardship or limited access to quality education within the school's catchment area.

Human Capital Accumulation Index:

This study uses a Human Capital Accumulation Index to capture the long-term impact of road infrastructure on human capital development, specifically focusing on the transition from secondary to higher education. This school-level index, distinct from the World Bank's national-level Human Capital Index (HCI) (World Bank, 2019), measures the proportion of students from each school who enroll in and complete a university program within a specified timeframe after finishing secondary school.

Drawing on the World Bank's definition of human capital as "the knowledge, skills, and health that people accumulate throughout their lives" (World Bank, 2019), a higher index value suggests greater success in preparing students for higher education and their potential for increased productivity and socioeconomic mobility. I construct this index by linking the student-level SABER 11 database with the SABER PRO database using unique student identifiers provided by ICFES.

Descriptive Statistics

Table 2 presents descriptive statistics for the treatment group (schools within 1500 meters of a road project) based on data from the year immediately preceding road construction (according to the date of signing of the concession contract). This table provides a snapshot of the schools before the intervention, capturing key characteristics and student outcomes.

Table 2: School Characteristics and Student Outcomes by Year: Treatment Group one period

	Outcome Variables		School Characteristics		Student Demographics		
Year	Math	Reading	Distance	Total Students	Child Labor Index	HCA Index	INSE
2006	-0.0436 (0.9918)	-0.133 (1.1881)	0.5052 (0.4150)	45.2995 (40.4329)	0.1652 (0.1420)		
2009	-0.2448 (0.9197)	-0.1202 (0.8600)	0.5543 (0.4130)	62.11628 (48.9306)	0.1534 (0.1269)		
2013	-0.1447 (0.9008)	-0.2808 (0.7966)	0.6748 (0.3905)	35.6000 (35.8399)	0.0968 (0.0756)	0.0874 (0.1286)	43.3514 (4.1608)
2014	-0.1541 (0.8774)	-0.0812 (0.8815)	0.5594 (0.4337)	44.1739 (39.2844)	0.1180 (0.1989)	0.1238 (0.1452)	43.2330 (4.0903)
2017	-0.4465 (0.8779)	-0.4473 (0.8653)	0.5425 (0.5018)	41.9375 (35.3881)	0.1612 (0.1348)	0.0822 (0.0986)	42.6148 (2.9828)
2019	-0.5376 (0.8426)	-0.5576 (0.8544)	0.4396 (0.4354)	35.3703 (32.1704)	0.1812 (0.1504)		42.3331 (3.7554)

Note: This table presents school characteristics and student outcomes for the treatment group (schools within 1500 meters of a road project), showing values from the year immediately preceding the road construction start date for each school (according to the date of signing of the concession contract). Math and reading scores are standardized using national means. Distance is the average Euclidean distance between the school and a road (km). Values in parentheses are standard deviations. INSE measures socioeconomic disadvantage (higher values indicate greater disadvantage). HCA Index is the Human Capital Accumulation Index.

These baseline characteristics provide a valuable context for understanding the potential impacts of improved road infrastructure on student outcomes. To further illustrate the characteristics of schools at the cusp of different construction milestones, Appendix Tables 11 through 14 present descriptive statistics for math and reading scores for the sample of schools in the year immediately preceding the achievement of the 0%, 10%, 50%, and 100% road completion milestones, respectively. This provides a snapshot of performance levels just before each key stage of intervention used in my subsequent DiD analyses.

As seen in Table 2, the average standardized math score is -0.262, and the average standardized reading score is -0.270, indicating that students in these schools generally performed below the national average prior to road construction. The average school size was 40.75 students, with the average distance from the nearest planned road to the school of 0.546 km. The average Child Labor Index was 0.146. The HCA Index has an average of 0.098 for the 2013, 2014, and 2017 cohorts (tracking of students for this metric began in 2012, and the index requires time for students to complete a bachelor's degree). INSE, available since 2013, has an average of 42.88. These baseline characteristics provide a valuable context for understanding the potential impacts of improved road infrastructure on student outcomes, which will be examined through a rigorous causal analysis in the subsequent sections.

4 Empirical Strategy

This section outlines the empirical strategy employed to estimate the causal impact of improved road infrastructure on educational outcomes in Colombia. I aim to isolate the effect of road access from other factors that might influence student performance. To achieve this, I utilize a staggered difference-in-differences (Staggered DiD) approach, exploiting the variation in the timing of road project completion across different schools.

4.1 Staggered DiD and Estimator Choice

The staggered DiD method is a common approach for estimating the dynamic effects of treatments with varying adoption times. However, as Goodman-Bacon (2021); Sun and Abraham (2021) demonstrate, conventional two-way fixed effects (TWFE) regressions can suffer from "contamination" due to the staggered adoption. In a standard TWFE model, early-treated units can inadvertently serve as controls for later-treated units even after the early-treated units have already been affected by the treatment. This occurs because the TWFE estimator essentially averages the effects of treatment across all treated units and time periods. In the presence of treatment effect heterogeneity, the coefficient on a specific relative period indicator (e.g., two years after treatment) can be influenced by the past treatment effects experienced by earlier adopters, leading to potentially biased estimates of the effect for the later-treated units. This issue, known as "treatment effect contamination," is particularly problematic when treatment effects vary across units or over time.

To address this issue, I employ the staggered DiD estimator proposed by Sun and Abraham (2021). This estimator accommodates various forms of treatment effect heterogeneity and accounts for potential violations of parallel trends in the short term (Construction time), as long as they converge in the long run (after the construction is done). Its flexibility is crucial here, given the likely variation in road improvement impacts across schools. Moreover, the S&A estimator aggregates cohort-specific treatment effects, enhancing the policy relevance of the findings.

Several other estimators have been proposed for handling staggered DiD, but their assumptions limit their applicability to this study. For instance, de Chaisemartin and D'Haultfœuille (2020) and Cengiz, Dube, Lindner, and Zipperer (2019) rely on a "stacked regression" approach that, while addressing some heterogeneity concerns, may not be ideal for capturing the dynamic and evolving nature of road construction impacts. Callaway and Sant'Anna (2021) and Borusyak, Jaravel, and Spiess (P2021) propose methods that are more flexible but often require strong assumptions about functional form or the availability of pre-treatment covariates. Gardner (P2022) and Dettmann, Giebler, and Weyh (2020) offer alternative two-stage DiD approaches, but their reliance on specific control groups or time periods might not be suitable for analyzing the long-term and spatially-varying effects of road improvements. Roth and Sant'Anna (2021) propose a method best suited when the timing of treatment is almost random, an assumption that doesn't fully apply to this research. Furthermore, while recent advancements allow for continuous treatment DiD (e.g., Callaway, Goodman-Bacon, and Sant'Anna, 2024), limitations in the granularity of consistently available construction progress data across all projects and years in my dataset make the direct application of such estimators infeasible at this time. My milestone-based approach (detailed in Section **??**) is therefore chosen to provide the most rigorous analysis possible with the available information.

Assumptions and Justification:

The validity of the staggered DiD approach hinges on the parallel trends assumption, which posits that the treatment and control groups would have exhibited similar trends in the absence of the intervention. Figures 8 and 9 depict pre-treatment trends in standardized math and reading scores, revealing largely parallel trends across most cohorts. While minor deviations are observed in the small 2010 and 2011 cohorts (3-10 and 1-3 schools, respectively), their limited size (fewer than 100 students combined) makes them susceptible to random fluctuations. The remaining, substantially larger cohorts (over 700 students on average) demonstrate consistent pre-treatment trends, supporting the parallel trends assumption. This observation is corroborated by the pre-treatment trends estimated using the Sun and Abraham (2021) estimator (Figures 11 and 15).

Further context on the pre-milestone academic performance for schools included in each of my stage-specific analyses (0%, 10%, 50%, and 100% completion) can be found in Appendix Tables 11 through 14.

Anticipation effects are unlikely given the commercially driven nature of road projects in Colombia. Route selection prioritizes connecting major commercial centers (Sanchez, 2022), with minimal consideration given to school locations. The final route is often determined only after the concession contract is awarded, making it difficult for schools to anticipate road improvements. The extended period of feasibility studies and public bidding (averaging 1.5 years) further supports the quasi-random nature of school placement relative to future road projects.

However, as shown in 14 and 18, some of the coefficients on the leads of the treatment variable (i.e., the periods before road construction completion) are statistically significant. This suggests that the treatment and control groups may have been on different trajectories prior to the implementation of the road improvement project. This finding challenges the validity of the parallel trends assumption, which is a core requirement for the difference-in-differences design.

Furthermore, to address these concerns about potential violation of the parallel trends assumption, I used Sun and Abraham (2021) approach, an estimator that stands out due to its flexibility in accommodating various forms of treatment effect heterogeneity and its ability to account for potential violations of parallel trends in the short term, as long as they converge in the long run.

4.2 Addressing Challenges: Continuous Treatment and Anticipation

Estimating the causal effect of road construction on education poses a unique challenge because the treatment (improved road access) is not a one-time event but a continuous process that unfolds over several years. Traditional DiD models, which assume discrete treatment times, are not well-suited to handle this continuous treatment dynamic. While ideally one might use a continuous measure of road construction progress, my dataset has limitations in the consistent granularity of such data across all projects and time periods, making the direct application of continuous treatment DiD estimators (e.g., Callaway, Goodman-Bacon, and Sant'Anna, 2024) currently infeasible.

To address this and still capture the evolving nature of the impact, I propose analyzing the impact of road construction at four specific completion percentages: 0% (start of construction), 10%, 50%, and 100% (See Figure 5). Analyzing the impact at different completion percentages allows me to capture how the perceived benefits of education change as road construction advances, potentially reflecting the emergence of new economic opportunities, reduced transportation costs, and improved access to educational resources.

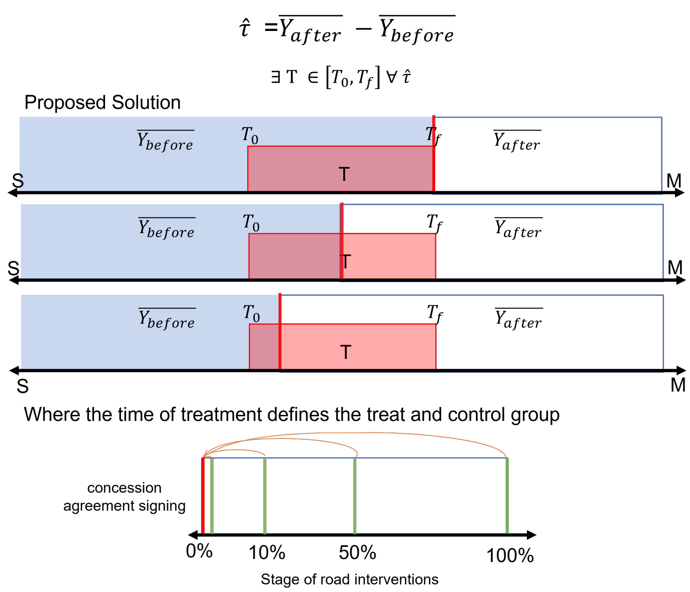


Figure 5: Addressing Continuous Treatment in Staggered DiD: Defining Treatment Groups Based on Road Completion Stages

Furthermore, by analyzing these distinct stages, I can leverage the flexibility of the Sun & Abraham (2021) estimator to strategically choose reference periods that skip the periods of active construction. This is particularly important because the parallel trends assumption might be most vulnerable during these periods, as construction activities could introduce temporary disruptions or changes in school attendance patterns. By focusing on periods before construction begins (0% completion) and after certain milestones are reached (10%, 50%, 100%), I can mitigate concerns about parallel trends violations during the construction phase itself. This approach allows me to isolate the effects of improved accessibility once a certain level of road functionality is achieved, rather than conflating those effects with the potentially disruptive impacts of ongoing construction. To address potential violations of the parallel trends assumption during active construction periods, I strategically choose reference periods that focus on periods before construction begins and after specific milestones are reached. This helps to isolate the long-term effects of improved accessibility from the potentially disruptive short-term impacts of ongoing construction activities.

I estimate the following dynamic DiD model with school and time fixed effects:

$$Score_{c,t,j} = \sum_{\tau=-S}^{-2} \mu_{\varphi} \cdot D_{c,\tau} + \sum_{\tau=0}^{M} \mu_{\varphi} \cdot D_{c,\tau} + \sigma_t + \gamma_c + \varepsilon_{c,t} \tag{1}$$

Where:

$Score_{c,t,j}$ represents the standardized test score (math or reading) for school c in year t for subject j. μ_{φ} captures the effect of road construction on education in relative period φ. $D_{c,\varphi}$ is a set of dummy variables indicating the distance of each period from the treatment period, defined by the stage of road construction (10%, 50%, or 100% completion). σ_t represents time fixed effects to control for time-varying factors common to all schools. γ_c represents school fixed effects to control for unobserved school-specific factors. $\varepsilon_{c,t}$ is the error term, clustered at the school level to account for within-school correlation. The effect of road construction on education is captured by the coefficients μ_{φ}, which estimate the impact of road access at different time lags and leads relative to the chosen completion percentage. I consider a time window from -S to M to capture both pre-treatment and post-treatment effects.

4.3 Additional Outcomes and heterogeneities

To provide further evidence for the mechanisms linking road infrastructure to educational outcomes, I examine two additional outcomes: (1) Human Capital Accumulation, measured by students' enrollment and completion of higher education programs, (2) Child Labor, assessed using the Child Labor Index. Analyzing these outcomes will allow me to test whether road improvements lead to changes in long-term educational attainment, child labor participation, and the socioeconomic composition of schools as predicted by the mechanisms outlined in Section 5, which draw upon principles of human capital theory.

Heterogeneities Analysis by Distance:

To further investigate the localized effects of road infrastructure and rule out potential spillover effects, I conduct subgroup analyses based on distance bands. I divide schools into groups based on their distance to the nearest road project, with each band representing a 500-meter increment (0-500 meters, 500-1000 meters, 1000-1500 meters, and so on, up to 4000 meters). I then estimate our dynamic DiD model separately for each distance band to examine how the magnitude and significance of the treatment effects vary with proximity to the road.

By conducting subgroup analyses based on distance bands, I can investigate whether the effects of road improvements are concentrated in schools closest to the new roads, suggesting a stronger influence of reduced transportation costs and enhanced access to educational resources. This analysis will help to rule out potential spillover effects and provide more precise estimates of the localized impact of road infrastructure.

5 Mechanisms: How Road Infrastructure Shapes Educational Investment

This study examines how road infrastructure improvements influence educational outcomes in Colombia by altering the cost-benefit analysis that students and their families undertake when deciding on educational investments. My analysis builds upon Becker's Human Capital Model (HCM) (Becker, 1993), which posits that investment in education is a rational decision based on weighing the anticipated returns against the costs. The HCM framework views education as an investment in human capital, where individuals aim to maximize their future well-being by acquiring skills and knowledge.

Road improvements, I argue, shift this cost-benefit equation in three key ways. First, they reduce monetary and opportunity costs associated with education, in light of which attending schools is made more feasible and affordable by the lower transportation expenses. (Tom Hertz, Tamara Jayasundera, Patrizio Piraino, Sibel Selcuk, Nicole Smith, and Alina Verashchagina , 2007; Behrman, J. R., & Knowles, J. C. , 1999), what is more, this also frees up students' time for studying, as they spend less time commuting (Filmer, D., 2004). Second, better roads facilitate access to more resources such as better schools, quality teachers, and more quality inputs such as more modern materials or even the internet access. This is because road infrastructure provides an avenue for quality inputs and technologies in the same way it alleviates teachers shortages in rural areas by making easier the commute of qualified teachers and the transportation of goods to and from rural schools (Mzuza1 & Westhuizen, 2023). With the described increased accessibility, students from rural areas can have access to these resources and have more opportunities to succeed (Goolsbee & Guryan, 2006). Finally, improved accessibility also stimulates economic activity, creating new markets and job opportunities in rural areas (Asher & Novosad, 2020; Jacoby, 2000; Quintero & Sinisterra, P2022), which demonstrates the economic value of education and motivate students to invest more in their schooling.

Improved roads directly reduce the costs associated with education, particularly in rural areas. For instance, lower costs, resulting from reduced travel time and expenses, make it easier and more affordable for students to attend school regularly, as highlighted by news reports (Consonante, 2022; Pulzo, 2022; Tiempo, 2023a, 2023b). This reduction in monetary and non-monetary costs of attending school therefore translates into more time available for learning(Becker, 1993). This subsequently implies an increase in academic performance.

Furthermore, better roads facilitate the flow of educational resources to remote schools. Textbooks, teaching materials, laboratory equipment, and qualified teachers can reach these schools more easily, enhancing the quality of education provided and reducing indirect costs associated with attending poorly equipped schools (Khumalo & Mji, 2014; Zipporah M Mokaya, 2013). While my data do not directly observe changes in resource availability, the observed increase in standardized test scores (both math and reading) in schools near improved roads, as presented in Table 4, suggests that these schools may be benefitting from enhanced access to resources that support student learning.

Beyond reducing costs, road infrastructure improvements also indirectly influence the perceived benefits of education. New roads often stimulate economic activity, creating new markets and job opportunities (Asher & Novosad, 2020; Jacoby, 2000; Quintero & Sinisterra, P2022). This shift can demonstrate the economic value of education, motivating students to invest more in their schooling. In Colombia, this could lead to a shift away from agricultural labor, where child labor is prevalent, towards more formal sectors that value education. My study finds that road improvements are associated with a 3.21 percentage points reduction in child labor participation in areas near improved roads (see Table 6), suggesting that road infrastructure can contribute to a decline in child labor by altering local labor markets and increasing the perceived returns to education, aligning with findings from Fafchamps and Wahba (2006a).

Moreover, improved connectivity to urban centers can expose rural communities to new ideas, aspirations, and opportunities for higher education (R. Idei, Kato, & Morikawa, 2020; Mukherjee, 2012). My analysis shows a 4.82 percentage points increase in the proportion of students pursuing higher education following road improvements (see Table 5). This suggests that increased exposure to urban areas, facilitated by road infrastructure, can broaden student aspirations and bolster their motivation for higher education.

Central to this analysis is the understanding that decisions regarding educational investment are guided by a cost-benefit analysis. Households weigh the potential long-term benefits of education (represented by the Discounted Present Value of Benefits, or $\sum_{t=0}^{n} \frac{B_t}{(1+r)^t}$), against the upfront costs and ongoing expenses (represented by the Discounted Present Value of Costs, or $\sum_{t=0}^{n} \frac{C_t}{(1+r)^t}$). This decision rule can be expressed as follows:

$$\text{Invest if} \quad \sum_{t=0}^{n} \frac{B_t}{(1+r)^t} > \sum_{t=0}^{n} \frac{C_t}{(1+r)^t} \tag{2}$$

This framework aligns with the principles of the Human Capital Model, where investments in education are seen as yielding returns over an individual's lifetime (Schultz, 1988). The cost-benefit analysis of education can be better related to HCM if I consider that, a reduction in real (money) or opportunity (time) costs, combined with improvements in educational quality, are what leads to better academic outcomes, which in turn leads to higher incomes and better returns in time (Card, 1999).

My research demonstrates that road infrastructure investments can profoundly impact educational choices, not just by directly reducing costs, but also by fundamentally shaping the perceived benefits of education. By improving academic performance, road infrastructure indirectly enhances the likelihood of realizing greater benefits from education, making it a more compelling investment for individuals and families. My empirical analysis aims to quantify these dynamics, offering evidence for the crucial role of road infrastructure in promoting human capital development and fostering a brighter future for all.

6 Results

This section presents the empirical findings from my analysis of the impact of Colombia's road concession program on educational outcomes. To provide a robust benchmark for interpreting the magnitude of our estimated effects, I draw upon previous studies that have established typical effect sizes for educational interventions (Evans & Yuan, 2022; Kraft, 2020). I use these benchmarks (See Appendix A)as a guide for assessing the practical significance of our findings, considering both the magnitude and the direction of the estimated effects.

I begin by examining the impact of road concessions on student enrollment, a key factor in access to education. I then present the effects on standardized math and reading achievement, followed by an exploration of heterogeneity in treatment effects by distance. Finally, I present the results for my additional outcome variables, providing a more comprehensive assessment of the program's impact.

6.1 Changes in Student Enrollment

I investigate changes in school student enrollment patterns before, during, and after road construction. This is a critical step because systematic changes in enrollment could indicate that families are moving in response to the road improvements, potentially biasing my estimates of the impact on educational outcomes. Specifically, if families with a higher propensity for education are more likely to move near newly constructed roads, my results could be upwardly biased.

Furthermore, given the limited availability of schools in these areas, a significant influx of households would likely manifest as a detectable increase in enrollment rates during and after the road construction. Therefore, analyzing enrollment trends provides a valuable, albeit indirect, measure of potential endogenous household mobility.

To assess this potential for endogenous mobility, I construct an Enrollment Impact Index (EII) (See equation 6). A positive EII indicates an increase in enrollment, suggesting that more students are attending schools in the treatment area after the road improvements compared to schools that have not been treated yet. Table 3 presents the estimated ATT for the EII across different stages of road construction.

Table 3: Enrollment Impact Index (EII): Total Average Treatment Effects by Construction Stage

	Completion			
Stage	0%	10%	50%	100%
ATT Estimate	0.0069 (0.0473)	0.0499 (0.0433)	0.0971 (0.0441).	0.0059 (0.0224)
Adjusted R^2	0.3669	0.4468	0.5972	0.5648
Within R^2	0.3651	0.4445	0.5951	0.561
RMSE	0.2676	0.2668	0.1691	0.1998
Observations	1058	733	571	348
Fixed Effects	School ID , year			
S.E. Clustered by:	School ID, Road ID			

Note: This table presents the total average treatment effect on the treated (ATT) estimates for standardized reading scores at different stages of road construction completion, using the Sun & Abraham (2021) estimator. The EII measures the percentage change in enrollment from the pre-treatment period to the post-treatment period. The treatment group consists of schools located within 1500 meters of a road project. Standard errors (in parentheses) are clustered at the school and road ID level.
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

My analysis of the EII reveals that there is no consistent pattern of significant changes in student enrollment across different stages of road completion. This suggests that, overall, road construction does not lead to large, systematic shifts in student enrollment patterns that would strongly bias my treatment effect estimates.

However, the marginally significant positive ATT estimate at the 50% completion stage warrants further discussion. It is possible that some families may temporarily relocate to take advantage of short-term economic opportunities created during the active construction phase. However, the fact that this effect is not sustained upon completion suggests this mobility is transient and primarily related to the construction activity itself, rather than a long-term shift in residential patterns driven by the educational benefits of improved roads.

To further address the possibility of endogenous mobility, I conducted a robustness check examining changes in the socioeconomic characteristics of enrolled students. This analysis suggests that the socioeconomic conditions of students enrolling in schools do not significantly differ as road construction progresses (see Robustness Check: 6.5.1). This finding provides additional support for the assumption that the composition of the student population is not significantly changing due to the road construction.

These findings increase my confidence that the primary results, relating to math and reading scores, the Child Labor Index and the Human Capital Accumulation Index, are not substantially driven by systematic changes in household location decisions.

6.2 Impact of Road Concessions on Standardized Test Scores

The analysis reveals a dynamic relationship between road construction progress and standardized math and reading scores. Initially, schools located near planned road projects experience a decline in math scores, which may be attributed to an anticipation effect caused by disruptions and noise during the early stages of construction. This finding aligns with the disruptions noted in similar contexts by Yasar Avsar (2005) and Tomek and Urhahne (2022). The effect on reading scores is less pronounced, possibly due to the more individualized nature of reading activities. As construction progresses, these negative impacts diminish, with mixed and generally insignificant effects observed for both subjects. However, upon project completion, a clear positive impact emerges, with both math and reading scores showing improvement. Notably, the positive effect on math scores is more substantial compared to reading.

Table 4 presents the estimated total average treatment effects on the treated (ATT) for math and reading scores across various stages of road construction completion, derived using the Sun and Abraham (2021) estimator.

Table 4: Impact of Road Construction Progress on Standardized Test Scores

Completion Stage	**Math Score**	**Reading Score**	**Total Students**
0%	-0.1114 (0.0497)*	-0.0398 (0.0315)	118,143
10%	-0.0251 (0.0506)	0.0128 (0.0285)	97,020
50%	0.0341 (0.0307)	0.0070 (0.0121)	89,949
100%	0.1687 (0.0322)**	0.1123 (0.0308)*	70,535
Fixed Effects: School ID, year			
S.E. Clustered by: School ID, Road ID			

Note: This table presents the Total ATT estimates for standardized math and reading scores at different stages of road construction completion, using the Sun and Abraham (2021) estimator. The treatment group consists of schools located within 1500 meters of a road project. Standard errors are clustered at the school and road ID level.
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Before construction begins (0% completion), schools near future road projects exhibit a statistically significant decline in math scores, possibly reflecting a negative anticipation effect driven by concerns about disruptions, noise, and changes in the community. This decline is less evident and statistically insignificant for reading scores, suggesting potential subject-specific differences in vulnerability to external disruptions. Reading, being a more individualized and internalized activity, might be less affected by the anticipation of external changes.

As construction advances to 10% and 50% completion, the initial negative anticipation effect on math scores weakens, and the impact on both math and reading scores are positive, although often statistically insignificant, direction. This suggests a period of transition where potential benefits of improved access and reduced transportation costs are modulated by the ongoing construction. In addition to disruptions like noise and dust, labor market dynamics during construction could also contribute to this fluctuating effect. The construction activities themselves might create short-term, temporary jobs that draw the attention of some older students or family members away from schooling or incentivize dropouts with the need to supply family with income, potentially counteracting the positive effects of easier commutes for students and teachers. Further micro-level analysis and surveys could illuminate how road construction affects the specific labor changes and its interaction with human capital.

The full benefit of road construction materializes after project completion (100%). At this stage, students in schools near completed roads experience a statistically significant increase of 0.169 standard deviations in math scores and 0.112 standard deviations in reading scores. This magnitude aligns with moderate effect sizes reported in meta-analyses of educational interventions (Evans & Yuan, 2022; Kraft, 2020), suggesting a substantively meaningful impact. These positive and long-term effects likely stem from various mechanisms: improved access to better-resourced schools and educational materials, reduced transportation costs and commuting times leading to increased attendance and less fatigue, and increased student motivation stemming from new economic opportunities that emerge with improved connectivity.

Event study plots (Appendix Figures 11 to 14 and 15 to 18) illustrate the dynamic effects of road construction on math and reading scores. For math, the plots (and Table 17) reveal a consistent pattern: a statistically significant negative anticipation effect one year before construction, followed by insignificant effects during construction, and a positive and significant impact after completion (Figure 14). However, statistically significant coefficients in the pre-treatment period for math (Table 17, Figure 14) suggest a potential violation of the parallel trends assumption. This could be due to benefits like increased economic activity and improved school quality materializing in later construction stages even before official completion. Additionally, roads often become accessible before completion, potentially giving treatment group schools early advantages.

Reading scores follow a similar trend, but the anticipation effect is statistically insignificant. The event study plots (Figures 15 to 18) highlight the minimal impacts during construction. However, a clear positive trend emerges after completion (Figure 18), aligning with the significant ATT estimate at 100% completion and the estimations in Table 18.

These findings highlight the complex dynamics at play. While the disruptions of the construction process can temporarily obscure the benefits of improved road infrastructure, the long-term effects on both math and reading literacy are positive and meaningful. This underscores the importance of considering both short-term and long-term impacts when evaluating infrastructure projects, recognizing that the full benefits for educational outcomes may not be immediately apparent. However, the potential violation of the parallel trends assumption for math scores warrants further investigation and careful interpretation of the findings.

It's important to acknowledge that the presented increase in enrollment following road improvements may include students from more vulnerable socioeconomic backgrounds who previously faced significant barriers to accessing education. These students may initially enter the school system with lower levels of preparedness compared to their peers. However, average performance, particularly in mathematics, still increases significantly. This suggests that the positive effects of road improvements are potent enough to outweigh the potential downward pressure on average scores from the inclusion of these students. This may be driven by a combination of factors: the improved infrastructure itself facilitating more consistent attendance and study habits, and the influx of better resources into the schools (as previously discussed), enabling these institutions to more effectively support all students, regardless of their background.

6.3 Heterogeneity Analysis by Distance

To examine whether the impact of road construction varies with school proximity and to rule out potential spillover effects, I conduct a heterogeneity analysis by distance. I estimate the treatment effect separately for subgroups of schools located within specific distance bands from the nearest road project: 0-500 meters, 500-1000 meters, 1000-1500 meters, and so on, up to 2500 meters. For each distance band, this analysis is conducted separately for each of our four defined construction stages: 0% (start of construction), 10% completion, 50% completion, and 100% completion. Figures 4 and 5 present the ATT estimates for standardized math and reading scores, respectively, derived using the Sun & Abraham (2021) estimator. This approach allows me to assess how the treatment effect changes across different contexts and understand the spatial extent of the impacts.

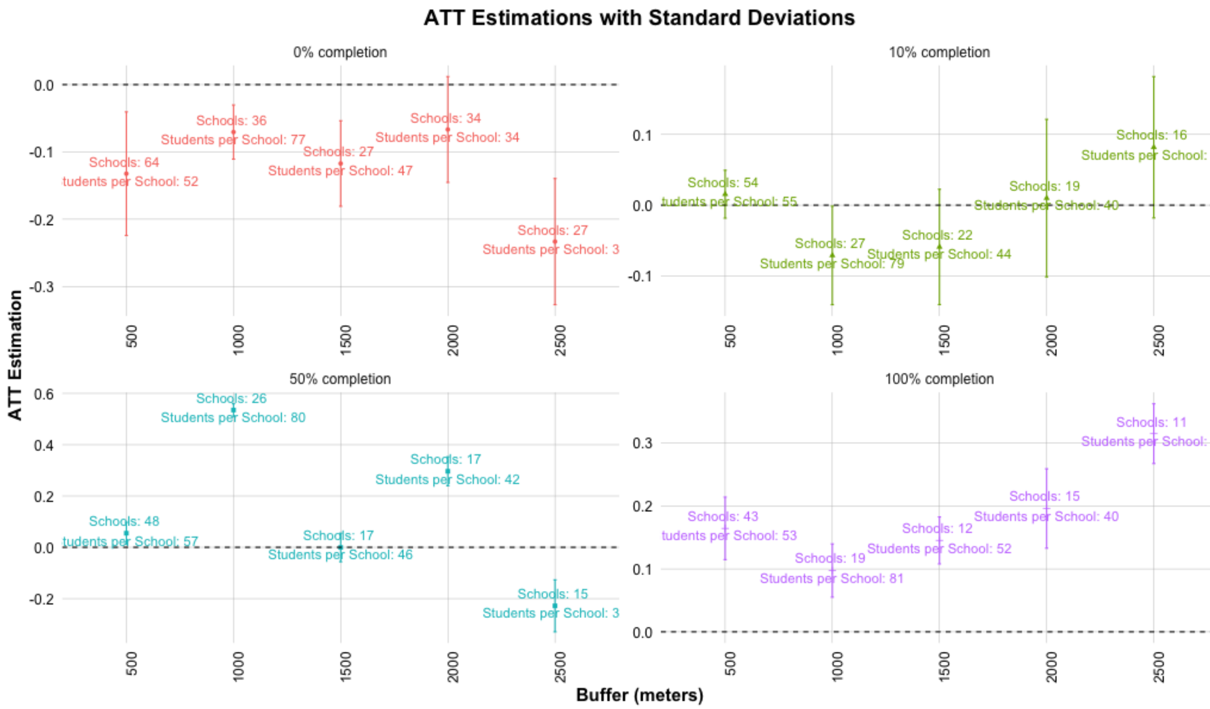


Figure 4: ATT Estimations for Math Scores across Distance Bands and Construction Stages. Each panel (0%, 10%, 50%, 100% Completion) represents a separate DiD analysis where the "treatment" is defined by reaching that specific construction milestone. Error bars represent 95% confidence intervals for the total ATT. Each data point reflects the estimated ATT at different distances from the road for that specific milestone analysis.

Analyzing the impact of road construction across different distances reveals patterns depending on the stage of construction referenced. When referencing the start of construction (0% completion stage), Figures 4 (panel a) and 5 (panel a) indicate a consistent negative anticipation effect on both math and reading scores for schools within 2500 meters of the planned project. This effect is most potent in the 2500-meter band, suggesting amplification at a slight distance from the immediate construction zone. As construction begins and reaches the 10% completion milestone (Figures 4 and 5), these negative anticipation effects generally diminish, becoming statistically insignificant across most distance bands for both subjects.

The patterns become more complex when referencing the 50% completion milestone (Figures 4 and 5). For both math and reading scores, the impacts vary by school location, with some distance bands showing positive effects while others display negative effects. This underscores the variability of impacts during the active, mid-construction phase.

The picture clarifies significantly when referencing full road completion (100% completion stage). For math scores, Figure 4 (panel d) shows a consistent pattern of positive and statistically significant effects emerging across all distance bands. Contrary to initial expectations, the largest estimated effects were identified in the more remote schools (between 2000 and 2500 meters), even though sample sizes for these estimates were often smaller than for closer buffers. In contrast, for reading scores at 100% completion (Figure 5), statistically significant positive effects only appear for schools in the 500-meter and 1000-meter bands. This localized positive impact might reflect easier access to reading-specific resources concentrated near the completed road. These effects on reading are, however, smaller in magnitude compared to those identified for math, potentially indicating weaker mechanisms linking road improvements to reading literacy outcomes.

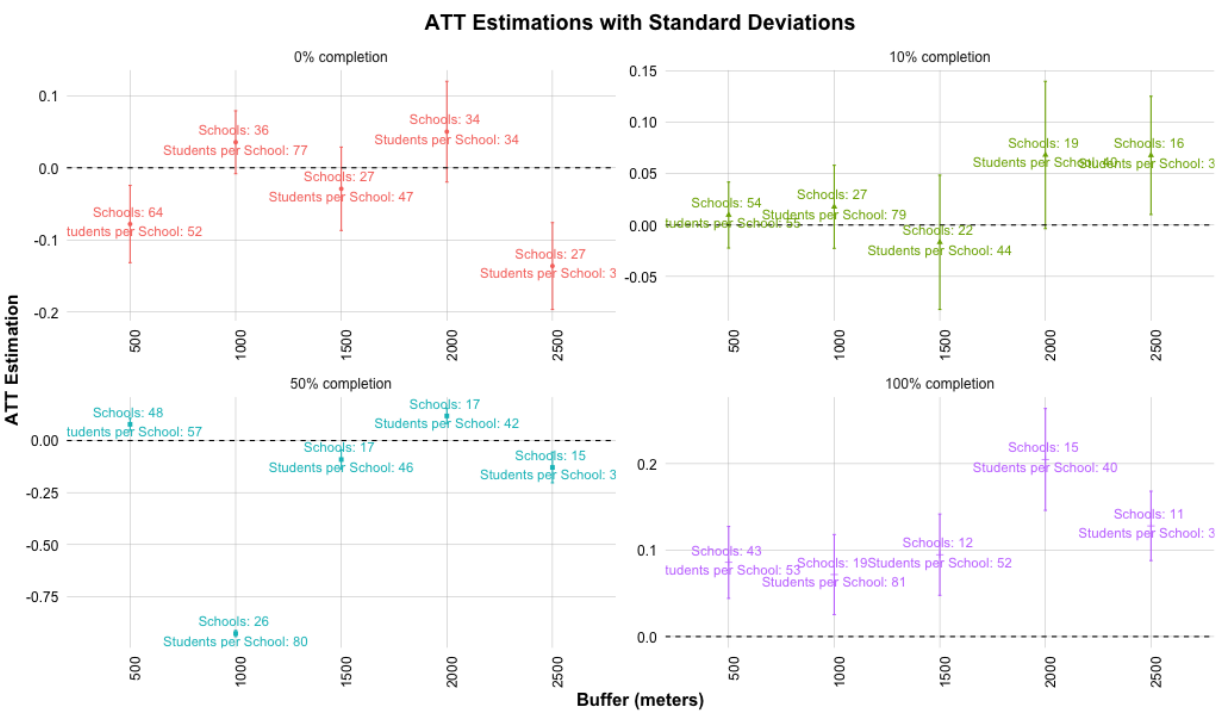


Figure 5: ATT estimations with standard deviations for reading literacy scores across distance bands and construction stages. Error bars represent 95% confidence intervals for the total ATT. Each data point reflects the estimated ATT at different distances, considering the number of schools and the average number of students per school.

This heterogeneity analysis provides key insights. First, it reveals the complex and localized nature of how road construction impacts educational outcomes, with effects varying by both distance and the specific stage of construction being referenced. Second, the analysis provides evidence against widespread, uniform spillover effects; instead, impacts appear to depend on unobserved heterogeneities within different locations that may warrant specific research. Finally, these results suggest that the proximity of schools to the intervention plays a significant role, indicating the need to carefully consider the effect of school location in causal impact evaluations. Policymakers should consider the distance of schools when planning road projects, potentially implementing targeted interventions to mitigate negative effects and ensure that schools further from the road also benefit from the improved infrastructure.

Furthermore, to address potential concerns regarding the influence of multiple omitted reference periods in the Sun & Abraham (2021) event study design (as discussed in Section 4.2), Appendix A.5 presents a robustness check (Figures 27 and 28). In this supplementary analysis, the ATT estimates for these distance-based heterogeneities are recalculated where the identification of the treatment effect for each milestone primarily relies on the year immediately preceding that milestone (t-1) as the reference. The overall patterns observed in these appendix figures remain broadly consistent with the main heterogeneity findings presented above, suggesting that the main conclusions are not unduly sensitive to the specific construction of reference periods in the primary S&A event study estimations.

6.4 Impact on Additional Educational Outcomes

6.4.1 Human Capital Accumulation

Table 5 presents the estimated average treatment effects on the treated (ATT) for the Human Capital Accumulation Index, representing the proportion of students transitioning from secondary to higher education. These estimates are derived using the Sun & Abraham (2021) estimator to assess the dynamic impact of road construction across different completion stages.

Table 5: Impact of Road Concessions on Human Capital Accumulation Index

	Completion			
Stage	0%	10%	50%	100%
ATT Estimate	-0.0048 (0.0141)	-0.06 (0.0308).	0.0004 (0.022)	0.0482 (0.0013)*
Adjusted R^2	0.7071	0.7088	0.7118	0.7723
Within R^2	0.7066	0.708	0.711	0.7713
RMSE	0.0861	0.0871	0.0865	0.0792
Observations	1901	1045	1029	681
Fixed Effects	School ID , year			
S.E. Clustered by:	School ID, Road ID			

Note: This table presents the average treatment effect on the treated (ATT) estimates for the Human Capital Accumulation Index at different stages of road construction completion, using the Sun & Abraham (2021) estimator. The treatment group consists of schools located within 1500 meters of a road project. Standard errors (in parentheses) are clustered at the school and road ID level.
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

At baseline, the Human Capital Accumulation Index was 0.098 (Table 2), meaning approximately 10% of students transitioned to higher education before road construction. The most pronounced and statistically significant effect emerges at the 100% completion stage, where the ATT indicates that for every 100 students, I see almost 5 more students transitioning to higher education (4.82 percentage points). While benchmarks for this specific outcome are limited, this suggests that, on average, completing road construction is associated with a meaningful increase in access to higher education for students near the improved roads.

To gain a deeper understanding of this dynamic, Figures 23 to 26 (in the Appendix) present the estimated ATTs for each relative time period across the different stages of road construction.

It is important to reconcile the positive impact observed throughout HCA with the EII analysis (Table 3). This can be done by focusing on the differences in what each index measures, highlighting that while the HCA focuses on the impact of the road completion over the transitioning students to a higher education; the EII focuses on changes in student enrollment throughout the road completion phases. Therefore, the EII increase in the early completion stages and the drop when they are fully operational may be linked with temporarily workforce changes in the construction sites, which is not necessarily a contradiction to an estimated positive effect in students transitioning to a higher education levels.Consequently, this does not constitute an issue for the main analysis.

This finding suggests that anticipated benefits of improved road infrastructure, such as enhanced access to higher-quality schools and new economic opportunities, encourage students to invest in higher education. However, these effects take time to materialize, primarily appearing after road projects are fully completed. The dynamic patterns in the event study plots and the relatively small sample size at the 100% completion stage (681 observations) suggest directions for further investigation.

6.4.2 Impact on Child Labor

Table 6 presents the estimated average treatment effects on the treated (ATT) for the Child Labor Index, capturing the proportion of students in each school who report being engaged in work. These estimates are derived using the Sun & Abraham (2021) estimator. To visualize the dynamic relationship between road construction and child labor, I also present event study plots (Figures 19 to 22 in the Appendix).

Table 6: Impact of Road Concessions on Child Labor Index

	Completion			
Stage	0%	10%	50%	100%
ATT Estimate	0.0104 (0.0155)	-0.008 (0.0218)	0.0873 (0.0161)***	-0.0321 (0.0102)*
Adjusted R^2	0.7616	0.7738	0.7927	0.7855
Within R^2	0.7612	0.7734	0.7922	0.7849
RMSE	0.1009	0.0941	0.0876	0.0853
Observations	1901	1539	1360	1105
Fixed Effects	School ID , year			
S.E. Clustered by:	School ID, Road ID			

Note: This table presents the average treatment effect on the treated (ATT) estimates for the Child Labor Index at different stages of road construction completion, using the Sun & Abraham (2021) estimator. The treatment group consists of schools located within 1500 meters of a road project. Standard errors (in parentheses) are clustered at the school and road ID level.
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

At baseline, the Child Labor Index was 0.146 (Table 2), meaning approximately 15% of students in the treatment group reported engaging in work prior to road construction. The results indicate that road construction progress affects child labor in two phases. At the 50% completion stage, I observe a statistically significant and positive effect (ATT estimate of 0.0873), suggesting a correlation between road construction and a temporary rise of child labor participation. In the other hand, a statistically significant negative effect at 100% completion (ATT estimate of -0.0321) suggests that in the longer-term, improved road infrastructure decreases child labor participation. That is, in a school with an average share of 15% of kids working, the new roads would might decrease the child labor to almost 11 students.

These findings suggest a potential link between road infrastructure and child labor, which is consistent with what was presented and explained in Section 6.3 suggesting that the job openings due to the road construction could be a reason for more child labour participation, while the finishing of the road implied a cut on the demand of jobs and a smaller opportunity cost of studying. Nevertheless, further research is needed to understand the specific mechanisms driving these changes. This should focus in analyze deeply the impacts of better conditions to engage a high and skilled labour.

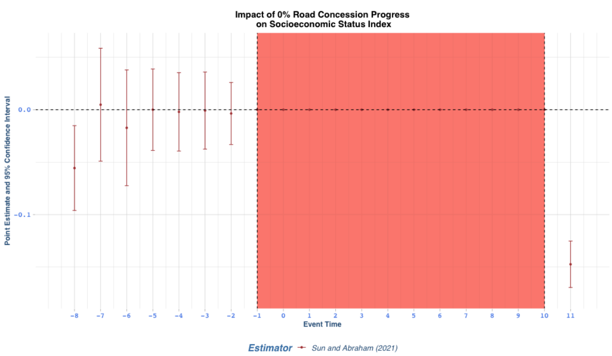
6.5 Robustness Checks

6.5.1 Robustness Check: Changes in socioeconomic conditions of enrolled student

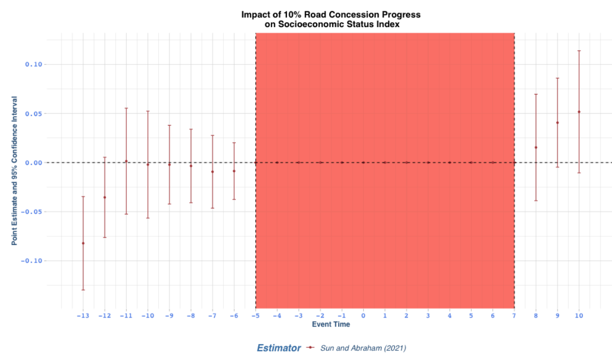
To assess whether road construction leads to changes in the socioeconomic composition of the student population, potentially biasing my results, I analyze the impact on the socioeconomic index (INSE) of enrolled students. I use the INSE as a proxy for household mobility. The logic is this: while I do not find statistically significant changes in enrollment to schools due road construction, as I show in the section 6.1, changes in the socioeconomic composition of school population could imply unobserved sorting of student populations to be taken into account for. For example, schools with an increase in the INSE index could suggest that new and more vulnerable families are moving to this schools area, meaning, the school context will be different even if the tests and characteristics of the impact are found to be the same. Figures 6 illustrate the estimated impact of road construction on the INSE at different stages of project completion.

A closer look at the figures reveals a nuanced pattern. At the 0% completion stage, the

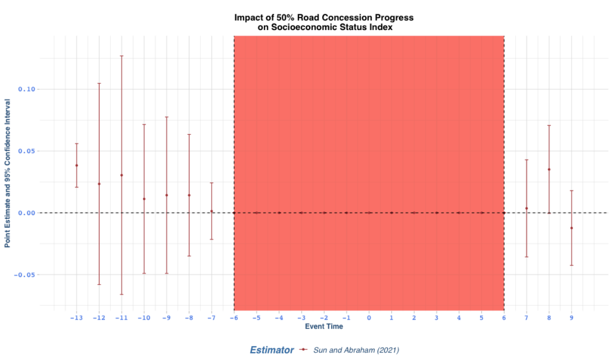
INSE appears to decrease, potentially suggesting that in anticipation of the road, the student population starts to be composed of a slight more wealthy families. However, there are not significant changes during road construction, as suggested by graphs of 10% and 50% of progress construction. But, the INSE seem to increase again at road completion. In the absence of overall increased enrollment, a rising INSE at completion could support the proposed mechanism: improved road access may enhance household income, allowing students to dedicate more time and resources to academic pursuits, thereby contributing to the observed improvements in test scores.



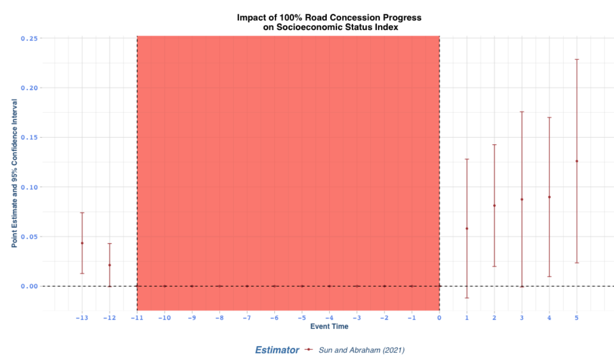
(a) Socioeconomic index (INSE) at 0% road concession progress.



(b) Socioeconomic index (INSE) at 10% road concession progress.



(c) Socioeconomic index (INSE) at 50% road concession progress.



(d) Socioeconomic index (INSE) at 100% road concession progress.

Figure 6: Estimated impact of road concession progress on the socioeconomic index (INSE) of enrolled students at different project completion stages.

Given the limitations, the fact that the INSE is statistically similar in school during the reference stages support the assumption that it is the road construction, as it benefits are materializing after the completion (and more significantly) for those schools that already reach their completion the unique source of changes in the observed outcomes. These results strengthen confidence in the robustness of our primary findings and help support its internal validity.

6.5.2 Robustness Check: Callaway and Sant'Anna (2021) Estimator

To assess the robustness of my findings and explore the potential influence of different modeling assumptions on the estimated effects, I employ the Callaway and Sant'Anna (2021) estimator (C&S) as an alternative to the Sun and Abraham (2021) estimator (S&A). While both estimators are designed to address the challenges of staggered DiD, they differ in their assumptions and how they handle potential violations of those assumptions.

The C&S estimator requires strict parallel trends in the immediate pre-treatment period for each group, which, if violated, can introduce bias. It estimates the instantaneous treatment effect per group per period but doesn't account for the evolution of effects over time or the cumulative impacts across construction stages.

In contrast, the S&A estimator, used in our analysis, permits short-term deviations from parallel trends as long as they align in the long term. It captures treatment effect heterogeneity across groups and time, and it aggregates effects across construction periods, offering a more dynamic and comprehensive impact assessment.

Table 7 presents the estimated treatment effects on standardized math and reading scores using the Callaway and Sant'Anna (2021) estimator.

Table 7: Impact of Road Construction Progress on Standardized Test Scores: Callaway and Sant'Anna (2021) Estimator

	Completion			
Stage	0%	10%	50%	100%
Math Score	-0.017 (0.0224)	0.1341 (0.0251)**	-0.1384 (0.1021)	0.1358 (0.0278)**
Reading Score	-0.0769 (0.0236)***	0.1176 (0.0252)***	-0.0301 (0.1002)	0.0311 (0.0291)
Observations	118143	97020	89949	70535
Fixed Effects	School ID, year			
S.E. Clustered by:	School ID, Road ID			

Note: This table presents the average treatment effect on the treated (ATT) estimates for standardized math and reading scores at different stages of road construction completion, using the Callaway and Sant'Anna (2021) estimator. The treatment group consists of schools located within 1500 meters of a road project. Standard errors (in parentheses) are clustered at the school and road ID level.
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 7 presents the estimated treatment effects on standardized math and reading scores using the C&S estimator to assess the robustness of the main findings. While the C&S estimator confirms a positive, albeit statistically insignificant, impact of road completion (100% stage) on math scores, it shows no significant effect on reading scores, unlike the S&A results. This difference potentially indicates that the positive effect on reading may be more sensitive to the stricter parallel trends assumption inherent in the C&S methodology.

These findings highlight the inherent complexities of analyzing staggered treatment adoption and the importance of carefully considering the assumptions underlying each estimator. While both the C&S and S&A estimators are powerful tools for addressing this challenge, they operate under different assumptions about parallel trends and treatment effect heterogeneity. The discrepancies spotted between the two estimators, particularly for reading scores, do not necessarily invalidate our main findings. Instead, they underscore the robustness of our results for math scores, which remain consistently positive and significant regardless of the estimator used. For reading scores, the sensitivity to the estimator choice suggests a more nuanced and potentially delayed impact. This highlights the need for further research to explore the specific mechanisms through which road infrastructure affects reading literacy and to investigate the sensitivity of these results to different assumptions about parallel trends and the dynamic nature of treatment effects. However, the consistent positive effects on math scores, even under the stricter assumptions of the C&S estimator, strengthen our confidence that improved road infrastructure has a meaningful and positive impact on educational outcomes in Colombia.

6.5.3 Robustness Check: Wald Pre-test on Pre-treatment Coefficients

To formally assess the parallel trends assumption, I conduct a Wald pre-test of the joint significance of the pre-treatment coefficients, following Callaway and Sant'Anna (2021). Table 8 presents the resulting p-values for math and reading scores across different completion stages. The generally non-significant p-values, particularly for the crucial 0% and 100% completion stages, provide statistical support for the assumption of parallel pre-trends, reinforcing the validity of our Difference-in-Differences approach.

Table 8: P-value for pre-test of parallel trends assumption, Callaway and Sant'Anna (2021)

	Completion			
Stage	0%	10%	50%	100%
Wald Test P-Value				
Math Score	0.39184	0.008	0.03526	0.65075
Reading Score	0.45603	0.00033	0.00165	0.69435

Note: This table presents p-values from a Wald test of the joint significance of pre-treatment coefficients in the dynamic Difference-in-Differences model, following the methodology outlined in Callaway and Sant'Anna (2021). The Wald test assesses the null hypothesis that pre-treatment trends are the same for treated and control groups. A non-significant p-value (typically above 0.05 or 0.10) supports the assumption of parallel pre-trends. Lower p-values indicate evidence against parallel pre-trends, suggesting potential pre-existing differences between groups before road construction.

6.5.4 Robustness Check: Distance-Based Control Group

To further assess the sensitivity of my results to the choice of control group and explore the potential for spillover effects identified in my heterogeneity analysis, I re-estimate my model using schools located more than 3000 meters away from the road project as an alternative "never treated" group. This approach helps address concerns about unobserved factors that might be driving pre-treatment differences between schools near and far from road construction. Table 9 presents the estimated treatment effects on standardized math and reading scores using this alternative control group.

Table 9: Impact of Road Construction Progress on Standardized Test Scores (Alternative Controls)

	Completion			
Stage	0%	10%	50%	100%
Math Score	-0.0788 (0.0445).	0.0152 (0.05)	0.0351 (0.0263)	0.1165 (0.0442)*
Reading Score	-0.0435 (0.0323)	0.0125 (0.0275)	-0.0147 (0.0121)	0.0612 (0.0298).
Observations	118143	97020	89949	70535
Fixed Effects	School ID, year			
S.E. Clustered by:	School ID, Road ID			

Note: This table presents the average treatment effect on the treated (ATT) estimates for standardized math and reading scores at different stages of road construction completion, using the Sun and Abraham (2021) estimator. Standard errors (in parentheses) are clustered at the school and road ID level. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The results reveal that the positive and significant effect of road completion on math scores persists, albeit with a slightly smaller magnitude (0.1165 standard deviations). This suggests that the impact on math achievement is robust to different control group choices and that the positive effects observed up to 2500 meters in the heterogeneity analysis are unlikely due to spillovers from the treatment group. However, the effect on reading scores is no longer statistically significant, indicating potential sensitivity to unobserved factors correlated with distance. This finding aligns with the heterogeneity analysis, where the positive impacts on reading scores were concentrated within a shorter distance band (500-1000 meters). This pattern could reflect a more localized impact of road improvements on reading literacy, potentially due to factors like access to libraries or community literacy programs that are more prevalent closer to the road.

Interestingly, the C&S estimator finds significant positive effects at the 10% completion stage for both math and reading, a pattern not observed in the main analysis using the S&A estimator. This difference likely arises from the C&S estimator's limitations in handling continuous treatment and its reliance on only the last pre-treatment period for comparison. At the 10% completion stage, the treatment group already experiences some effects of the ongoing road construction. However, the C&S estimator compares this group to schools that are near the road but haven't yet experienced any construction progress, even if those schools are just slightly behind in the construction timeline (e.g., at 7% or 2% completion). This creates a biased comparison, as the C&S estimator effectively includes some treatment effects in its "control" group, leading to the identified sensitivity and potentially spurious positive effects at this stage.

6.5.5 Robustness Check: Alternative Distance Thresholds

To ensure my main findings are not sensitive to the specific choice of the 1500-meter radius for defining the treatment group itself, I re-estimate the model using alternative distance thresholds: 500 meters, 1000 meters, and 2000 meters. In contrast to the heterogeneity analysis in Section 6.3, where I analyzed impacts within fixed distance bands, this robustness check assesses the aggregate effect of road construction on all schools within a varying radius of the road, evaluating the sensitivity of the estimated treatment effect to the definition of the treated group. This will clarify the external validity of the results.

Table 10 summarizes the results of this robustness check, presenting the ATT estimates for math and reading scores at different stages of road completion using these alternative thresholds.

Table 10: Impact of Road Construction Progress on Standardized Test Scores (Alternative Distance Thresholds)

		Completion			
Outcome	Distance (m)	0%	10%	50%	100%
Math Score	500	-0.1323 (0.0918)	0.0155 (0.0339)	0.055 (0.0424)	0.1643 (0.0497)*
Math Score	1000	-0.1108 (0.0487)*	-0.0179 (0.0462)	0.0582 (0.0296).	0.1446 (0.0241)**
Math Score	1500	-0.1114 (0.0497)*	-0.0251 (0.0506)	0.0341 (0.0307)	0.1687 (0.0322)**
Math Score	2000	-0.1017 (0.0524).	-0.0202 (0.0587)	0.0696 (0.0315).	0.1456 (0.035)**
Reading Score	500	-0.078 (0.0536)	0.0097 (0.0321)	0.0782 (0.0289)*	0.0858 (0.0416).
Reading Score	1000	-0.0417 (0.0299)	0.0181 (0.0216)	0.0797 (0.0112)***	0.0883 (0.0258)*
Reading Score	1500	-0.0398 (0.0315)	0.0128 (0.0285)	0.007 (0.0121)	0.1123 (0.0308)*
Reading Score	2000	-0.0307 (0.0352)	0.0184 (0.031)	0.0223 (0.0133)	0.0976 (0.0356)*

Note: This table presents the ATT estimates for standardized math and reading scores at different stages of road construction completion using the Sun and Abraham (2021) estimator and alternative distance thresholds for defining the treatment group. Standard errors (in parentheses) are clustered at the school and road ID level.
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

My findings exhibit that the positive and significant effect of road completion (100% stage) on both math and reading scores remains generally consistent across the different distance thresholds, see table 10. This suggests that the conclusion that the benefits of improved road access on math and reading are not affected for the criteria of distance selection can be generalizable with 1500m as well as when considering the schools from 0 to 500, or the schools from 0 to 1000 as the schools from 0 to 2000. Therefore this results strengthen my confidence in the validity of these results.

My findings indicate a high degree of consistency across the different distance thresholds. The positive and significant effect of road completion (100% stage) on both math and reading scores remains evident regardless of the radius used. This suggests that the positive impacts of improved road access on educational outcomes extend beyond a narrowly defined treatment area. Interestingly, the significance of the effect on math scores with reference treatment period at the 0% completion stage diminishes as the distance threshold increases. This suggests that the negative effect might be more localized and concentrated closer to the road project.

In the opposite direction, I notice a significant change in impact at 10% completeness, where the positive effect is no longer evident. Therefore, this suggests that the results are not generalizable and must be interpreted according to the school's proximity.

This robustness check strengthens my confidence in the generalizability of my findings and indicates that the estimated effects are not influenced by arbitrary choices of distance thresholds. The consistent positive effect of road construction on both math and reading scores, regardless of the specific proximity criteria, strengthens the conclusion that improved road infrastructure meaningfully contributes to better educational outcomes in Colombia.

7 Conclusions

This study provides compelling evidence that Colombia's road concession program, a Public-Private Partnership initiative designed to improve the national road network, has yielded positive and significant impacts on educational outcomes in public schools. By employing a staggered difference-in-differences approach that accounts for the gradual rollout of road construction projects, I find that road improvements lead to a notable increase in student performance on the SABER 11 standardized test, particularly in mathematics.

My analysis reveals that positive effects emerge on both math and reading literacy scores after road projects are completed, suggesting that the benefits of improved access, reduced transportation costs, and increased economic opportunities take time to materialize. While the estimated magnitude of the impact on math scores appears larger than that on reading literacy, a formal test reveals that this difference is not statistically significant ($p = 0.204$). This suggests that the road concession program has a positive impact on both educational outcomes, and that the best policy approach would likely be to consider broader factors (overall educational benefit) rather than focusing on subject-specific interventions in the context of road construction. Further research is still needed to confirm the potential for subject-specific mechanisms.

Furthermore, my analysis reveals a significant correlation between road completion and child labor participation. While this finding suggests that improved economic opportunities for adults, facilitated by better road connectivity, might reduce the reliance on child labor, further investigation is needed to confirm this causal link. It is possible that this association also reflects other unmeasured factors influencing child labor dynamics during the road construction process. Additionally, I find an increase in the proportion of students pursuing higher education after road improvements, indicating that road infrastructure could have a lasting impact on human capital accumulation.

My findings remain robust across several rigorous robustness checks, including alternative estimators Callaway and Sant'Anna (2021), different control groups, and varying distance thresholds for defining the treatment group. This strengthens my confidence in the causal interpretation of the results and highlights the generalizability of the positive effects observed.

These findings hold important implications for policymakers considering PPPs as a mechanism for promoting human capital development. My study demonstrates that well-designed road concession programs can contribute to significant and lasting improvements in educational outcomes, particularly in areas historically hindered by poor transportation infrastructure. However, careful consideration should be given to the potential for subject-specific differences in impacts, the importance of addressing potential anticipation effects during the construction phase, and the need to monitor the long-term sustainability of the benefits. Further research should investigate the complex interplay between road infrastructure development and child labor dynamics, exploring the potential roles of household income, alternative employment opportunities, and other factors influencing child labor decisions.

The findings of this study offer valuable insights for policymakers seeking to leverage infrastructure development for educational progress. Prioritizing road improvements in educationally underserved areas, particularly through well-structured public-private partnerships, can yield significant and lasting benefits for student learning, and is associated with reduced child labor, and can promote higher education aspirations. However, policymakers must adopt a long-term perspective, acknowledging the dynamic nature of these impacts and mitigating potential disruptions during the construction phase. Moreover, integrating road infrastructure development with broader education policies that address subject-specific needs, teacher quality, and resource allocation will maximize the transformative potential of these investments. Finally, a commitment to sustainable road construction practices is crucial to ensure that the educational gains achieved are maintained for future generations.

While this study provides compelling evidence for the positive impacts of road concession programs on education in Colombia, it's essential to acknowledge potential limitations. First, the staggered DiD approach relies on the assumption of parallel trends, which, despite robustness checks, might not perfectly hold in all cases. To address this concern, I re-estimated key results using an alternative control group consisting of schools located more than 3000 meters away from construction sites. The persistence of statistically significant results with this alternative control group strengthens confidence in the validity of my initial findings. Second, the study focuses primarily on publicly available, aggregate-level data. Although this is suitable for this project it will be very enriching to make a qualitative analysis to understand changes at the micro level .Third, the reliance on observational data means I cannot definitively rule out all potential sources of unobserved confounding, though the inclusion of fixed effects and sensitivity analyses mitigate this concern. Finally, while this study assesses a range of educational outcomes and labor participation, it might not capture the full spectrum of potential effects on community development or long-term economic mobility. Additional research using qualitative techniques is needed to estimate the long-term effects.

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A Appendix

Appendix A.1: Photographic evidence

Figure 7: Students from the rural area of El Toco in northern Cesar, Colombia, face challenges accessing school due to inadequate road infrastructure. Source: Ávila (2018)

Appendix A.2 Index Formulas

1. Rural access index:

$$RAI = \frac{\text{Rural Population within 2.5 km of an All-Season Road}}{\text{Total Rural Population}} \tag{3}$$

2. Child labor Index:

$$\text{CLI} = \frac{We_{s,t}}{E_{s,t}} \tag{4}$$

Where $We_{s,t}$ represents the number of students in each school s who reported being engaged in any form of paid work at the time t, and $E_{s,t}$ is the total of students.

3. Human Capital Accumulation Index:

$$\text{HCAI} = \frac{Ue_{s,t}}{E_{s,t}} \tag{5}$$

Where $Ue_{s,t}$ represents the number of students in each school s, who enrolled and completed a university program within a specific time frame after finishing secondary school at time t, and $E_{s,t}$ is the total of students.

4. Enrollment Impact Index (EII):

$$\text{EEI} = \frac{(E_{t+n} - E_t)}{E_t} \tag{6}$$

Where E_{t+n} represents the total enrollment in the school at time $t + n$ (after treatment) and E_t represents the total enrollment in the school at baseline time t.

Appendix A.3 Data and Descriptive Statistics

Table 11: Descriptive Statistics of School Academic Performance One Year Prior to the 0% Road Construction Milestone (Start of Construction)

Variable	Overall (Mean (SD))	Overall N	2006	2007	2009	2010	2013	2014	2015
Mathematics	-0.14 (0.86)	6620	-0.16 (0.86)	-0.24 (0.89)	-0.69 (0.48)	-0.18 (0.75)	-0.14 (0.84)	-0.13 (0.86)	0.18 (0.95)
Reading Literacy	-0.19 (0.90)	6620	-0.20 (0.91)	-0.45 (0.86)	0.05 (0.74)	-0.33 (0.92)	-0.02 (0.93)	-0.20 (0.87)	-0.05 (0.92)

Note: This table presents mean math and reading literacy scores (with standard deviations in parentheses) and sample sizes (N) for schools included in the 0% completion stage analysis. Data are shown for the year immediately preceding the start of physical road construction near these schools, broken down by the year this pre-construction period occurred. "Overall" statistics are across all cohorts for this 0% milestone. Scores are standardized.

Table 12: Descriptive Statistics of School Performance One Year Before Completion of 10%

Variable	Overall (Mean (SD))	Overall N	2010	2011	2013	2015	2016	2018	2019	2020
Mathematics	-0.18 (0.93)	6559	-0.09 (0.92)	-0.55 (0.89)	-0.42 (0.07)	-0.33 (0.69)	-0.38 (0.81)	-0.16 (0.94)	-0.97 (0.76)	0.13 (0.87)
Reading Literacy	-0.22 (0.95)	6559	-0.10 (0.93)	-0.69 (0.97)	-0.14 (0.75)	-0.21 (0.69)	-0.39 (0.86)	-0.25 (0.94)	-0.88 (0.80)	-0.04 (0.88)

Note: This table presents mean math and reading literacy scores (with standard deviations in parentheses) and sample sizes (N) for schools included in the 10% completion stage analysis. Scores are standardized.

Table 13: Descriptive Statistics of School Performance One Year Before Completion of 50%

Variable	Overall (Mean (SD))	Overall N	2011	2014	2015	2017	2019	2020
Mathematics	-0.11 (0.89)	5694	-0.13 (0.78)	-0.07 (0.86)	-0.58 (0.75)	-0.34 (0.83)	-0.05 (0.95)	-0.14 (0.96)
Reading Literacy	-0.22 (0.90)	5694	-0.31 (0.95)	-0.18 (0.88)	-0.56 (0.85)	-0.42 (0.88)	-0.17 (0.95)	-0.21 (0.89)

Note: This table presents mean math and reading literacy scores (with standard deviations in parentheses) and sample sizes (N) for schools included in the 50% completion stage analysis. Scores are standardized.

Table 14: Descriptive Statistics of School Performance One Year Before Completion of 100%

Variable	Overall (Mean (SD))	Overall N	2015	2017	2019	2020
Mathematics	-0.20 (0.92)	4172	0.17 (0.86)	-0.14 (0.89)	-0.40 (0.83)	-0.68 (0.83)
Reading Literacy	-0.20 (0.95)	4172	0.13 (0.88)	-0.12 (0.92)	-0.42 (0.99)	-0.71 (0.86)

Note: This table presents mean math and reading literacy scores (with standard deviations in parentheses) and sample sizes (N) for schools included in the 100% completion stage analysis. Data are shown for the year immediately preceding the physical finish of road construction near these schools. Scores are standardized.

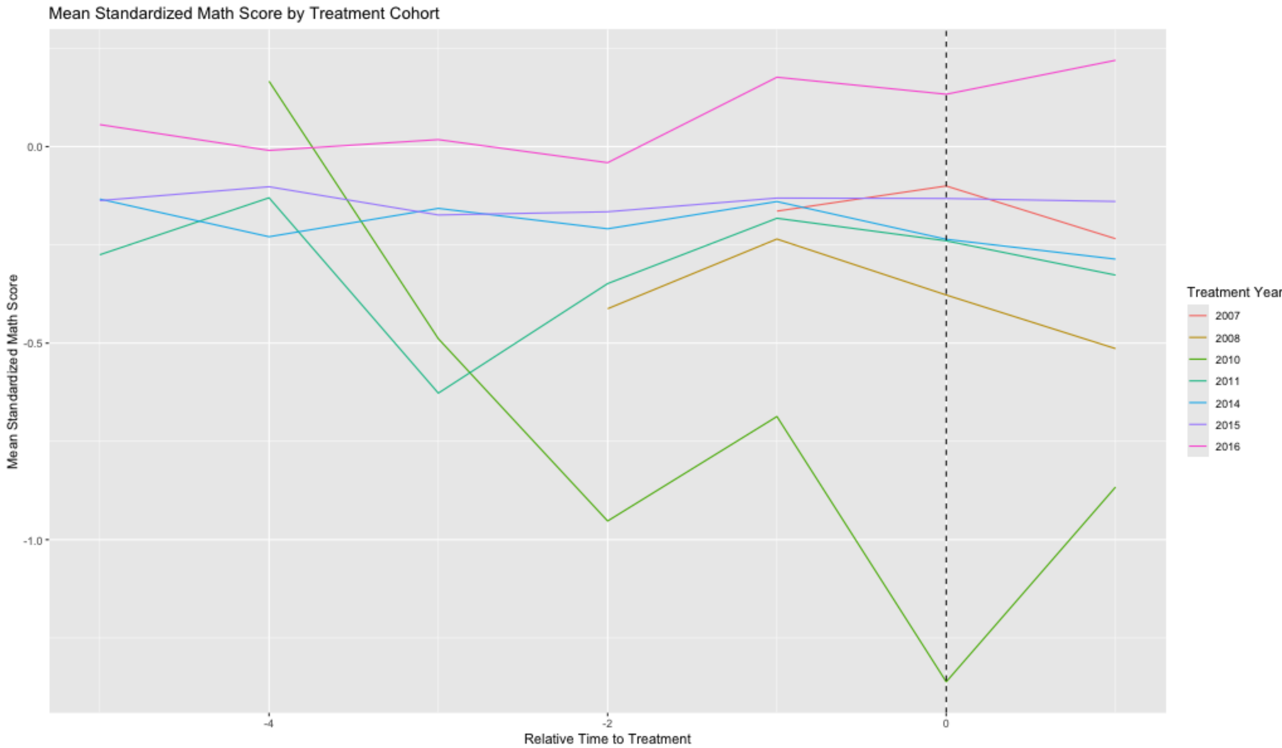

Figure 8: Mean Standardized Math Scores for Schools Near Road Projects, by Treatment Cohort (Pre-Treatment Period)

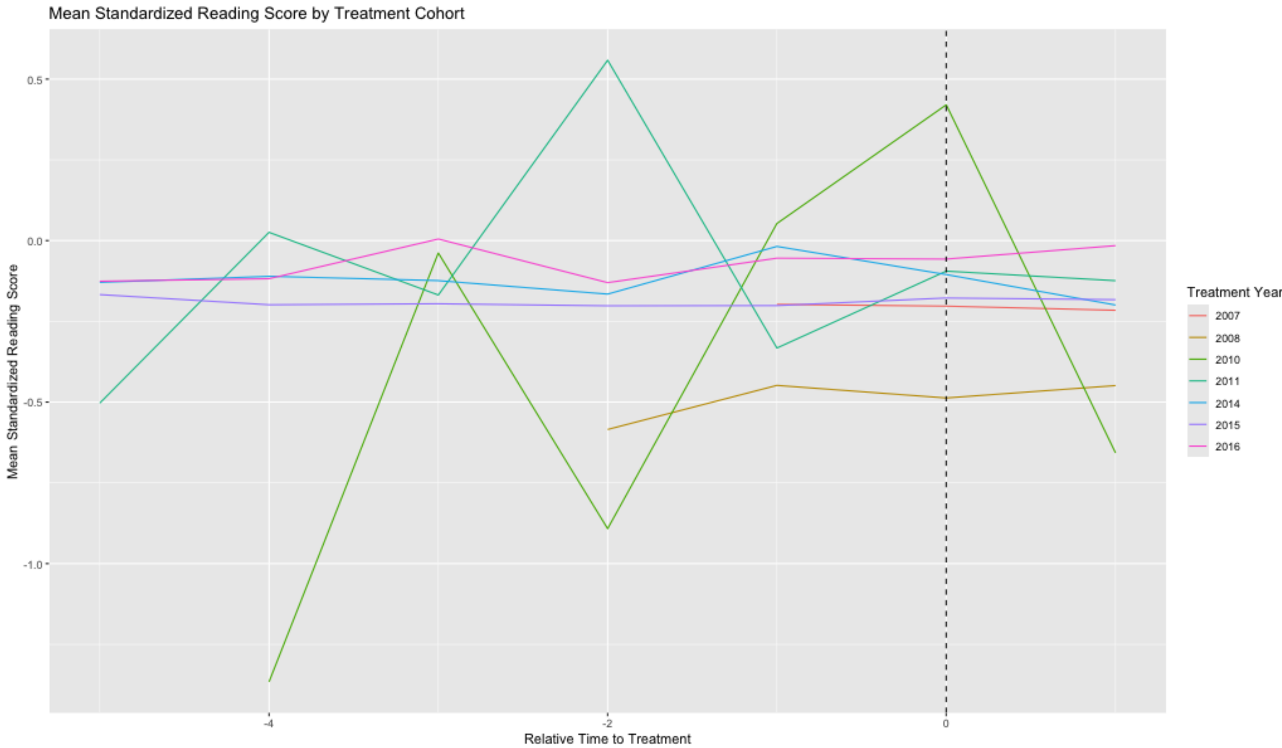

Figure 9: Mean Standardized Reading Scores for Schools Near Road Projects, by Treatment Cohort (Pre-Treatment Period)

(a) Correlation of Math Score (Source: PISA 2018) and Rural Access Index (WB 2019).

(b) Correlation of Reading Score (Source: PISA 2018) and Rural Access Index (WB 2019).

Figure 10: Relationship between PISA 2018 test scores (Math and Reading) and the Rural Access Index (World Bank, 2019).

Table 15: Concession Projects and their Details

Project	Concessionaire	Contract Number	Intervenor	SECOP/ANI Link
Bogotá - Siberia - La Punta - El Vino - Villeta	CONCESION SABANA DE OCCIDENTE S.A.	447-1994	SOCIEDAD CONCESION SABANA DE OCCIDENTE S.A.	https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=16-12-4627222
Bogota - Villavicencio	CONCESIONARIA VIAL DE LOS ANDES SAS COVIANDES S A S	444-1994	CONSORCIO INTERCONCESIONES	https://www.contratos.gov.co/consultas/detalleProcesoPTE.do?numCompromiso=716&subEntidad=24-13-00
Cartagena Barranquilla	CONSORCIO VIA AL MAR	503-1994	Consorcio Vía al Mar	https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=15-1-133681
Desarrollo Vial del Norte de Bogotá - DEVINORTE	UNION TEMPORAL DEVINORTE	664-1994	Consorcio ICITY	https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=13-12-2075308
Fontibon Facatativá Los Alpes	CONCESIONES CCFC S.A.	937-1995	CONSORCIO R&Q SERVINC	https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=15-1-132180
Desarrollo Vial del Oriente de Medellin - DEVIMED	DEVIMED S.A.	275-1996	CONSORCIO INTERCARRETEROS (Alcance básico) CONSORCIO HMV-SESAC (Adicional N° 14)	https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=14-4-3070110
Malla Vial del Valle y Cauca	UNION TEMPORAL MALLA VIAL DEL VALLE DEL CAUCA Y CAUCA	005-1999	CONSORCIO INTERCOL SP	https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=14-1-116960
Briceño -Tunja - Sogamoso	CSS CONSTRUCTORES S.A	377-2002	CONSORCIO CONCESIONES COLOMBIA	https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=16-1-156465
Bosa - Granada - Girardot	AUTOPISTA BOGOTA- GIRARDOT S.A.	040-2004		https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=16-1-156632
Zona Metropolitana de Bucaramanga	AUTOPISTAS DE SANTANDER S.A	002-2006		https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=14-1-117218
Cordoba - Sucre	AUTOPISTAS DE LA SABANA S.A.	002-2007	CONSORCIO EL PINO	https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=06-1-3368
Area Metropolitana de Cúcuta	CONCESIONARIA SAN SIMÓN S.A.	006-2007	Consorcio VELNEC-GNG	https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=06-1-6047

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Table 15 – continued from previous page

Project	Concessionaire	Contract Number	Intervenor	SECOP/ANI Link
Ruta Caribe	AUTOPISTAS DEL SOL S.A.	008-2007	CONSORCIO EPSILON VIAL	https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=06-1-5381
Girardot - Ibague - Cajamarca	CONCESIONARIA SAN RAFAEL S.A.	007-2007	CONSORCIO INTERCONCESIONES	https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=13-1-103191
Ruta del Sol sector - 1	CONSORCIO VIAL HELIOS	002-2010	Consorcio Zañartu MAB Velnec	https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=09-1-41316
Ruta del Sol sector - 2	CONCESIONARIO RUTA DEL SOL S.A	001-2010	CONSORCIO PROYECCIÓN VIAL PUERTO SALGAR	https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=09-1-41316
Ruta del Sol sector - 3	CONCESIONARIA YUMA S.A.	007-2010	CONSORCIO EL SOL	https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=10-
Transversal de las Américas - 1	CONSORCIO VÍAS DE LAS AMÉRICAS S.A.	008-2010		https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=09-1-49664
Transversal de las Américas - 2	TRANSVERSAL DE LAS AMÉRICAS S.A.S	009-2010		https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=09-1-49664
Vía Honda - Puerto Salgar - Villeta	RUTA DEL SOL - SECTOR 2 S.A.S.	003-2010		https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=09-1-49664
Ruta del sol sector - 3 (Yuma)	CONCESIONARIA YUMA S.A.S	007-2010	CONSORCIO PROYECCIÓN VIAL PUERTO SALGAR	https://www.contratos.gov.co/consultas/detalleProceso.do?numConstancia=09-1-49664

Note: This table provides details of various road concession projects in Colombia. It includes information about the project name, concessionaire, contract number, interventor (auditor), and a link to the SECOP or Portal ANI for further details.

Appendix A.4: Benchmark Effect Sizes for Educational Interventions from RCTs

Table 16 presents a summary of effect sizes categorized as small, moderate, and large, based on two comprehensive reviews of randomized controlled trials (RCTs) in education: Kraft (2020) and Evans and Yuan (2022).

Table 16: Benchmark Effect Sizes for Educational Interventions from RCTs (in Standard Deviations)

	Overall		Math	Reading	Enrollment
Effect Size	**Evans (2022)**	**Kraft (2020)**	**Evans (2022)**	**Evans (2022)**	**Evans (2022)**
Small	0.08	0.04	0.05	0.03	0.03
Moderate	0.10	0.10	0.07	0.14	0.06
Large	0.45	0.47	0.31	0.50	0.38
Number of Studies		96	199	269	33

Note: This table presents typical effect sizes, categorized as small, moderate, and large, based on reviews of randomized controlled trials (RCTs) in education. The effect sizes are reported in standard deviations (SD). The source of each effect size is indicated in the column headings.

Kraft (2020) analyzed 747 RCTs, while Evans and Yuan (2022) considered a larger sample of 96 studies. Both reviews found a median impact on overall educational outcomes of approximately 0.1 SD. When focusing specifically on learning outcomes, such as math and reading achievement, Evans and Yuan (2022) reports similar median effect sizes (0.07 SD for math and 0.14 SD for reading). The table also highlights the variation in effect sizes across studies, with the 25th and 75th percentiles for overall effects ranging from 0.04 SD to 0.1 SD in Kraft (2020) and 0.08 SD to 0.47 SD in Evans and Yuan (2022). Effects exceeding 0.45 SD are generally considered large.

Appendix A.5: Results

The results of the mathematics and reading score for all the different stages of construction are found in table 17 and 18, these estimation are based on Sun and Abraham (2021) estimation.

Math Results

Table 17: Dynamic DiD Estimation for Mathematics Scores

Relative Time Period	0% Completion	10% Completion	50% Completion	100% Completion
-15		-0.0925 (0.0971)	0.0323 (0.0241)	0.4326 (0.0784)
-14		-0.1043 (0.1121)	-0.2145 (0.1622)	0.4160 (0.0600)
-13		0.1505 (0.1475)	-0.1337 (0.2088)	0.3099 (0.0353)
-12		0.0562 (0.1751)	0.1806 (0.1230)	0.1667 (0.0239)
-11		0.1620 (0.1108)	0.1182 (0.1479)	0.00 (0.00)
-10	-0.0709 (0.0941)	0.1063 (0.1127)	0.0487 (0.0433)	0.00 (0.00)
-9	0.1342 (0.1326)	0.0725 (0.0563)	-0.2133 (0.0332)	0.00 (0.00)
-8	0.0849 (0.1310)	0.0324 (0.0621)	-0.0994 (0.0486)	0.00 (0.00)
-7	0.1097 (0.1004)	0.0322 (0.0814)	0.0460 (0.0308)	0.00 (0.00)
-6	0.1183 (0.0893)	0.0326 (0.0672)	0.00 (0.00)	0.00 (0.00)
-5	0.0964 (0.0548)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
-4	0.0478 (0.0604)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
-3	0.0092 (0.0743)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
-2	-0.0009 (0.0649)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
1	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.1250 (0.0177)
2	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.1390 (0.0391)
3	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.1325 (0.0234)
4	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.1574 (0.0481)
5	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.2401 (0.0327)
7	0.00 (0.00)	0.00 (0.00)	-0.0204 (0.0345)	
8	0.00 (0.00)	0.0352 (0.0631)	0.0755 (0.0320)	
9	0.00 (0.00)	-0.0663 (0.0540)	0.0549 (0.0330)	
10	0.00 (0.00)	-0.0467 (0.0493)		
11	-0.0788 (0.0721)			
12	-0.1099 (0.0507)			
13	-0.1258 (0.0379)			
14	-0.1383 (0.0441)			

Note: This table presents the average treatment effect on the treated (ATT) estimates for standardized math scores at key time periods relative to road construction completion, using the Sun & Abraham (2021) estimator. The treatment group consists of schools located within 1500 meters of a road project. Standard errors are in parentheses. The red "0.00 (0.00)" entries indicate reference periods that are excluded from the estimation to avoid collinearity and identify the treatment effects. The "never treated" cohorts, which only have negative RPs, act as the baseline reference group. The "always treated" cohorts have been removed from the analysis (represented by empty cells in the table).
Significance codes: *** p ¡ 0.001, ** p ¡ 0.01, * p ¡ 0.05, . p ¡ 0.1

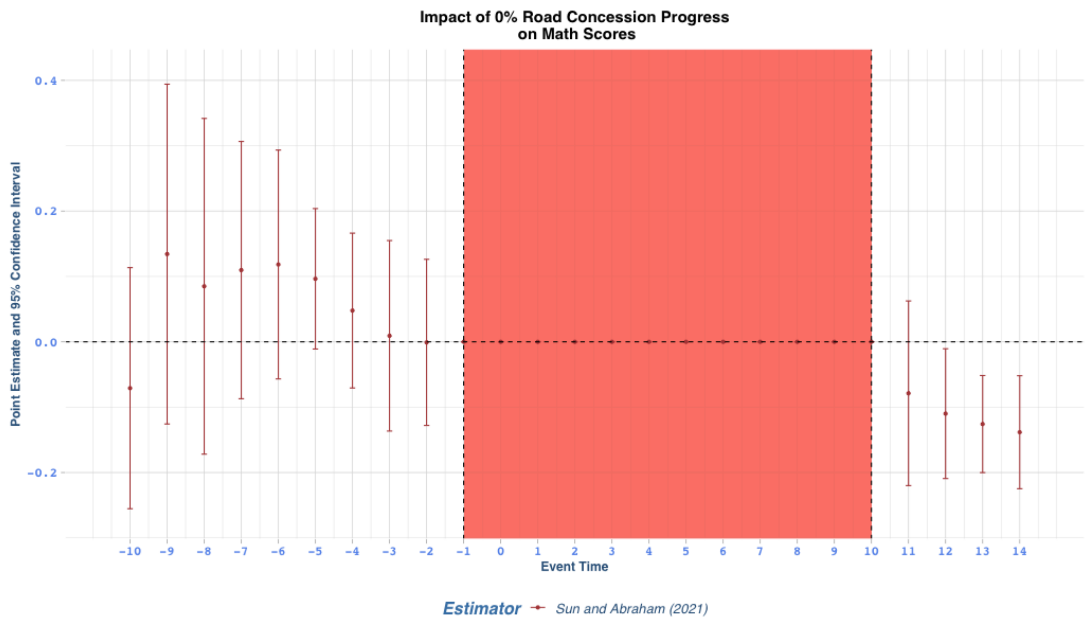

Figure 11: Impact of Road Construction on Standardized Math Scores (0% Completion). The shaded area indicates the reference periods excluded from the estimation to avoid collinearity and identify the treatment effect, as these periods are considered part of the road construction process.

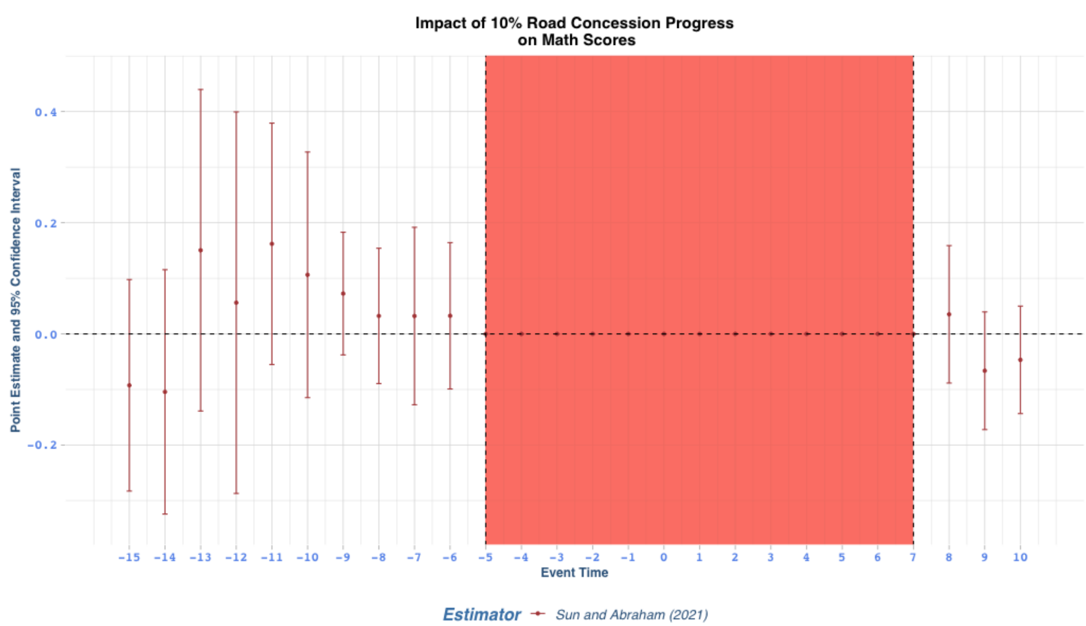

Figure 12: Impact of Road Construction on Standardized Math Scores (10% Completion). The shaded area indicates the reference periods excluded from the estimation to avoid collinearity and identify the treatment effect, as these periods are considered part of the road construction process.

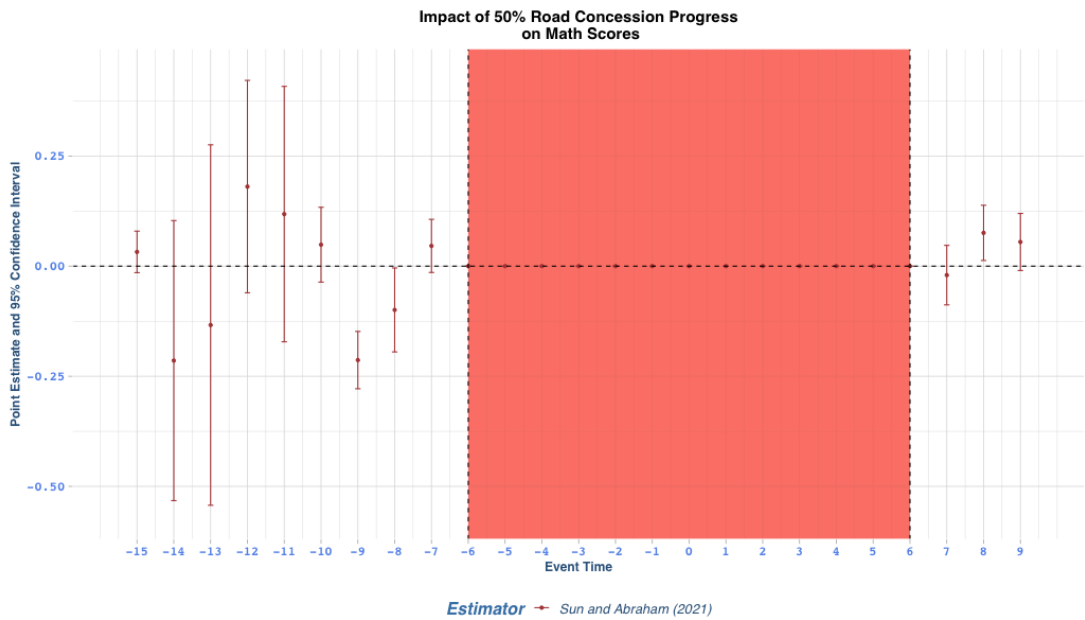

Figure 13: Impact of Road Construction on Standardized Math Scores (50% Completion). The shaded area indicates the reference periods excluded from the estimation to avoid collinearity and identify the treatment effect, as these periods are considered part of the road construction process.

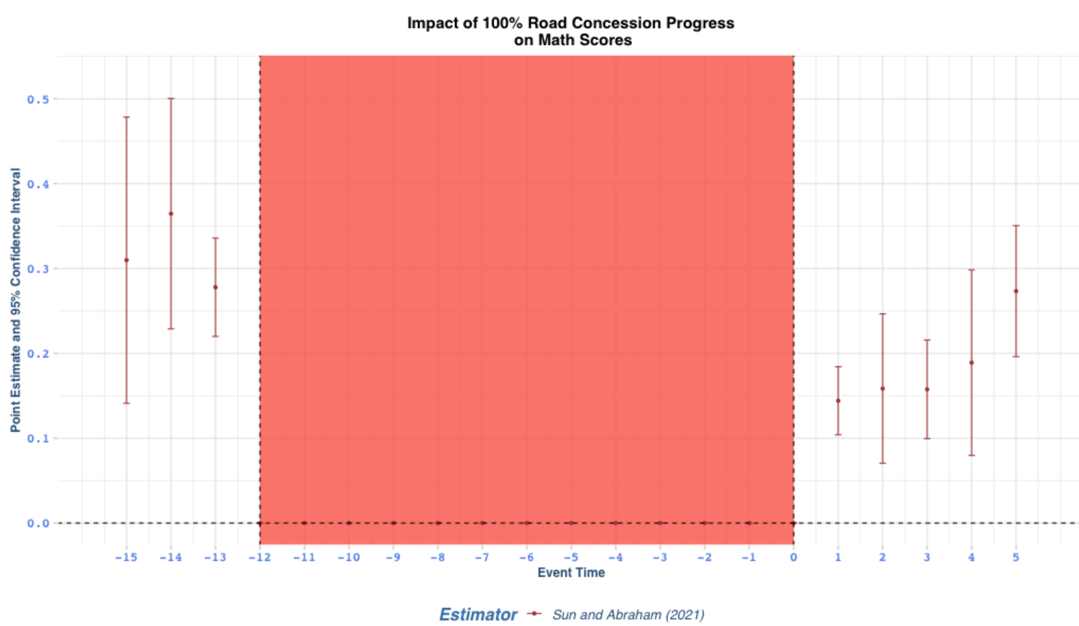

Figure 14: Impact of Road Construction on Standardized Math Scores (100% Completion). The shaded area indicates the reference periods excluded from the estimation to avoid collinearity and identify the treatment effect, as these periods are considered part of the road construction process.

Reading Results

Table 18: Dynamic DiD Estimation for Reading Scores

Relative Time Period	0% Completion	10% Completion	50% Completion	100% Completion
-15		-0.0925 (0.0971)	0.0323 (0.0241)	0.4326 (0.0784)
-14		-0.1043 (0.1121)	-0.2145 (0.1622)	0.4160 (0.0600)
-13		0.1505 (0.1475)	-0.1337 (0.2088)	0.3099 (0.0353)
-12		0.0562 (0.1751)	0.1806 (0.1230)	0.1667 (0.0239)
-11		0.1620 (0.1108)	0.1182 (0.1479)	0.00 (0.00)
-10	-0.0709 (0.0941)	0.1063 (0.1127)	0.0487 (0.0433)	0.00 (0.00)
-9	0.1342 (0.1326)	0.0725 (0.0563)	-0.2133 (0.0332)	0.00 (0.00)
-8	0.0849 (0.1310)	0.0324 (0.0621)	-0.0994 (0.0486)	0.00 (0.00)
-7	0.1097 (0.1004)	0.0322 (0.0814)	0.0460 (0.0308)	0.00 (0.00)
-6	0.1183 (0.0893)	0.0326 (0.0672)	0.00 (0.00)	0.00 (0.00)
-5	0.0964 (0.0548)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
-4	0.0478 (0.0604)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
-3	0.0092 (0.0743)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
-2	-0.0009 (0.0649)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
1	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.1250 (0.0177)
2	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.1390 (0.0391)
3	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.1325 (0.0234)
4	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.1574 (0.0481)
5	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.2401 (0.0327)
7	0.00 (0.00)	0.00 (0.00)	-0.0204 (0.0345)	
8	0.00 (0.00)	0.0352 (0.0631)	0.0755 (0.0320)	
9	0.00 (0.00)	-0.0663 (0.0540)	0.0549 (0.0330)	
10	0.00 (0.00)	-0.0467 (0.0493)		
11	-0.0788 (0.0721)			
12	-0.1099 (0.0507)			
13	-0.1258 (0.0379)			
14	-0.1383 (0.0441)			

Note: This table presents the average treatment effect on the treated (ATT) estimates for standardized math scores at key time periods relative to road construction completion, using the Sun & Abraham (2021) estimator. The treatment group consists of schools located within 1500 meters of a road project. Standard errors are in parentheses. The red "0.00 (0.00)" entries indicate reference periods that are excluded from the estimation to avoid collinearity and identify the treatment effects. The "never treated" cohorts, which only have negative RPs, act as the baseline reference group. The "always treated" cohorts have been removed from the analysis (represented by empty cells in the table).
Significance codes: *** p ¡ 0.001, ** p ¡ 0.01, * p ¡ 0.05, . p ¡ 0.1

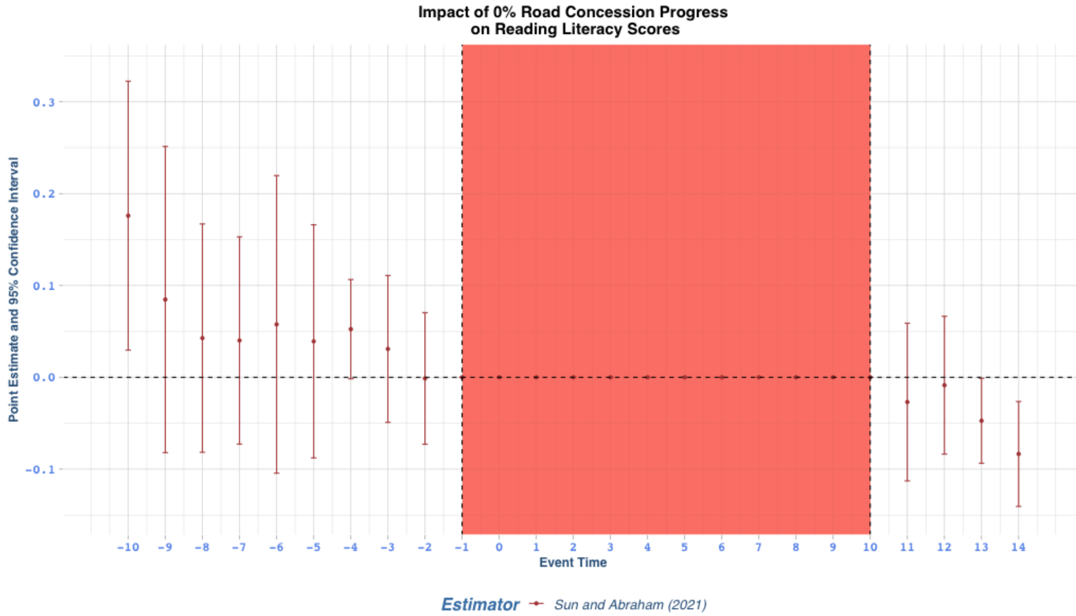

Figure 15: Impact of Road Construction on Standardized Reading Literacy Scores (0% Completion). The shaded area indicates the reference periods excluded from the estimation to avoid collinearity and identify the treatment effect, as these periods are considered part of the road construction process.

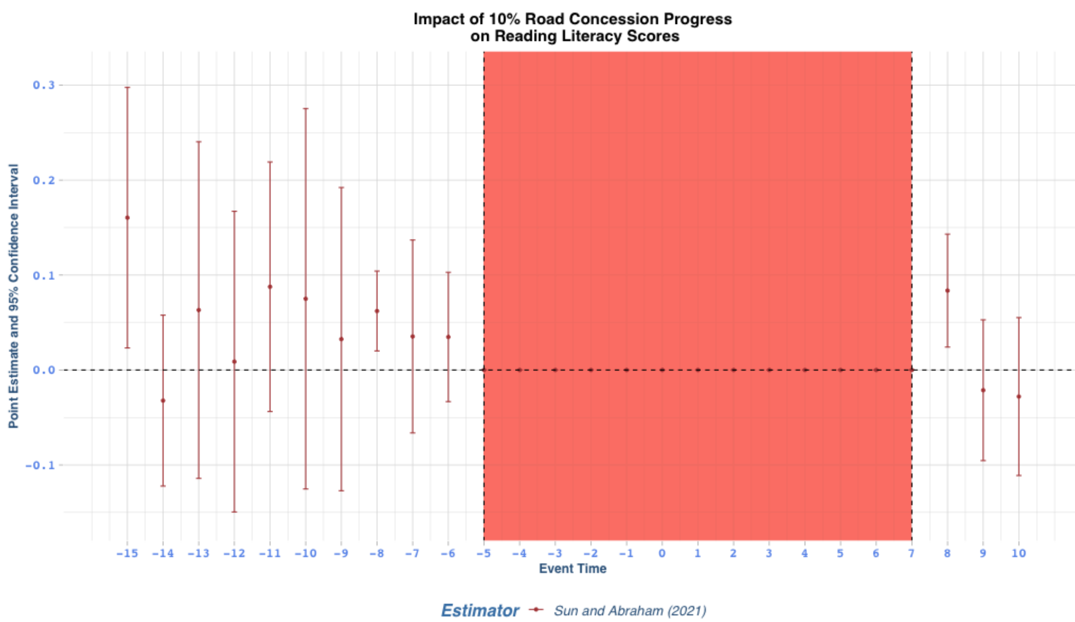

Figure 16: Impact of Road Construction on Standardized Reading Literacy Scores (10% Completion). The shaded area indicates the reference periods excluded from the estimation to avoid collinearity and identify the treatment effect, as these periods are considered part of the road construction process.

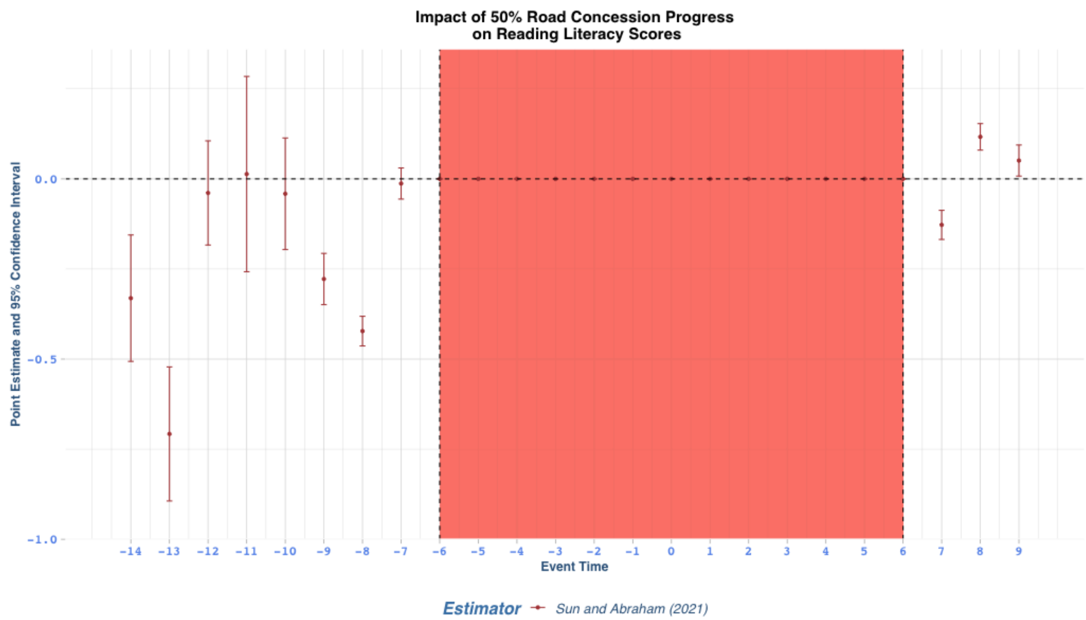

Figure 17: Impact of Road Construction on Standardized Reading Literacy Scores (50% Completion). The shaded area indicates the reference periods excluded from the estimation to avoid collinearity and identify the treatment effect, as these periods are considered part of the road construction process.

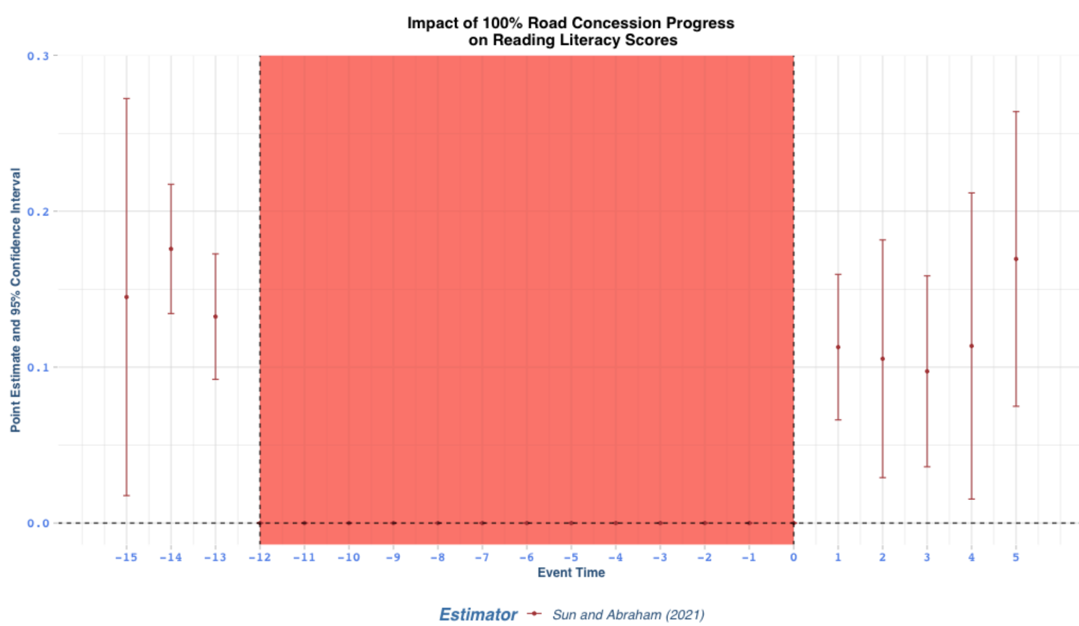

Figure 18: Impact of Road Construction on Standardized Reading Literacy Scores (100% Completion). The shaded area indicates the reference periods excluded from the estimation to avoid collinearity and identify the treatment effect, as these periods are considered part of the road construction process.

Child Labor Index

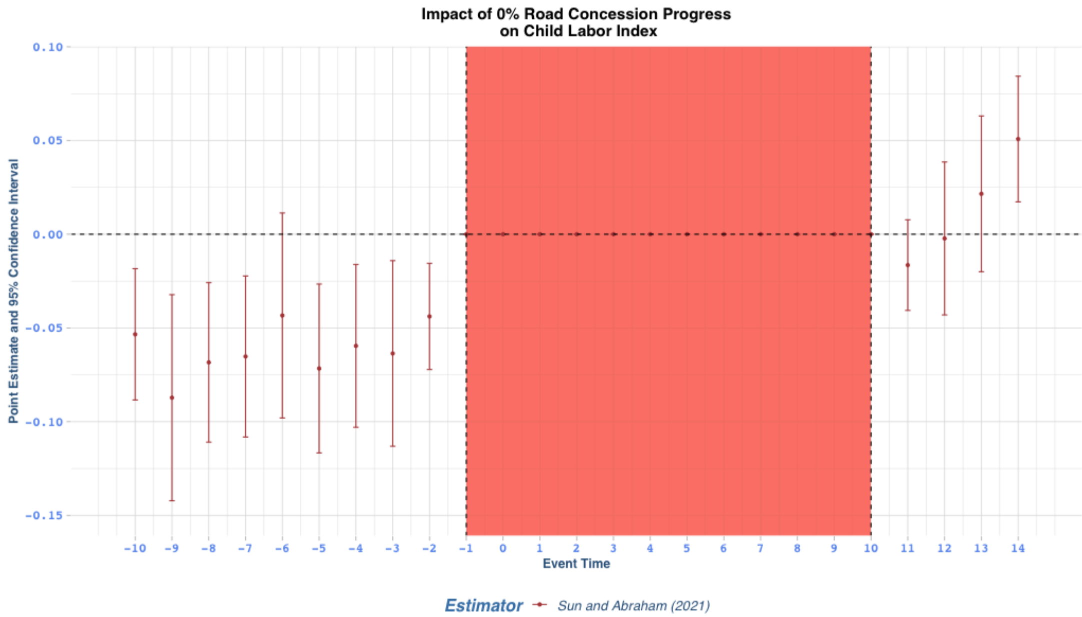

Figure 19: Impact of Road Construction on Child Labor Index (0% Completion). This figure shows the estimated average treatment effect on the treated (ATT) for the Child Labor Index in each year relative to the start of road projects. The shaded area indicates the reference periods excluded from the estimation. Error bars represent 95% confidence intervals.

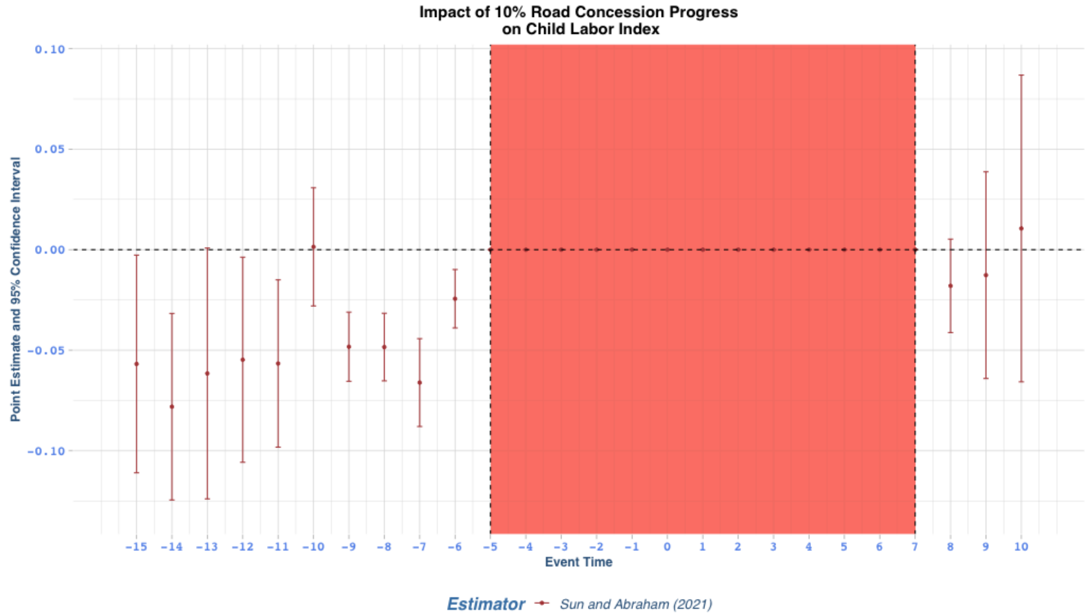

Figure 20: Impact of Road Construction on Child Labor Index (10% Completion). This figure shows the estimated ATT for the Child Labor Index in each year relative to the year when the road project reaches 10% completion. The shaded area indicates the reference periods excluded from the estimation. Error bars represent 95% confidence intervals.

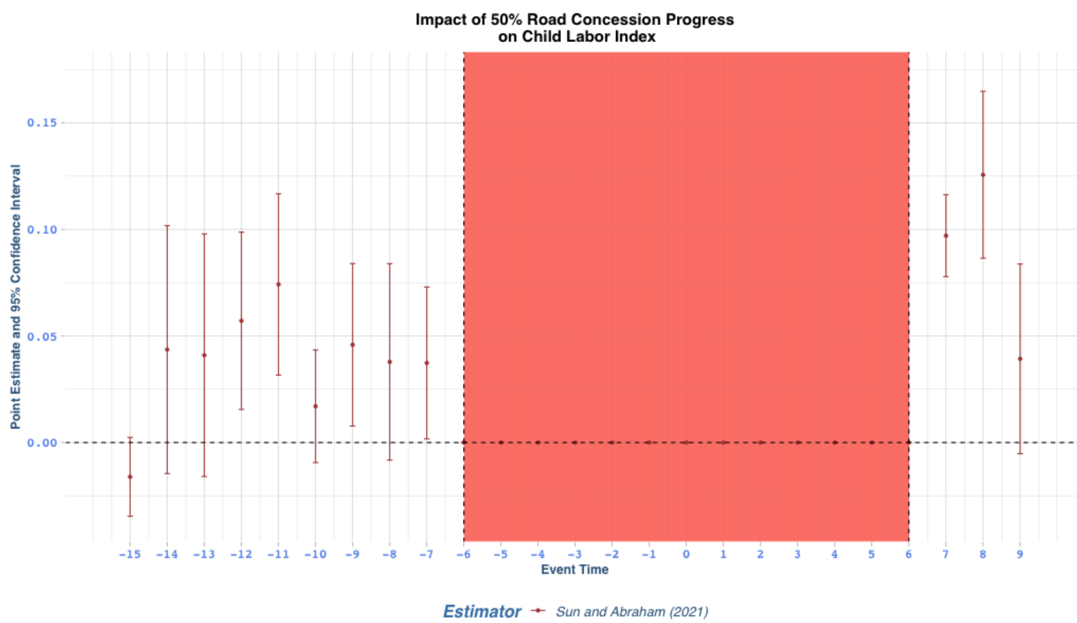

Figure 21: Impact of Road Construction on Child Labor Index (50% Completion). This figure shows the estimated ATT for the Child Labor Index in each year relative to the year when the road project reaches 50% completion. The shaded area indicates the reference periods excluded from the estimation. Error bars represent 95% confidence intervals.

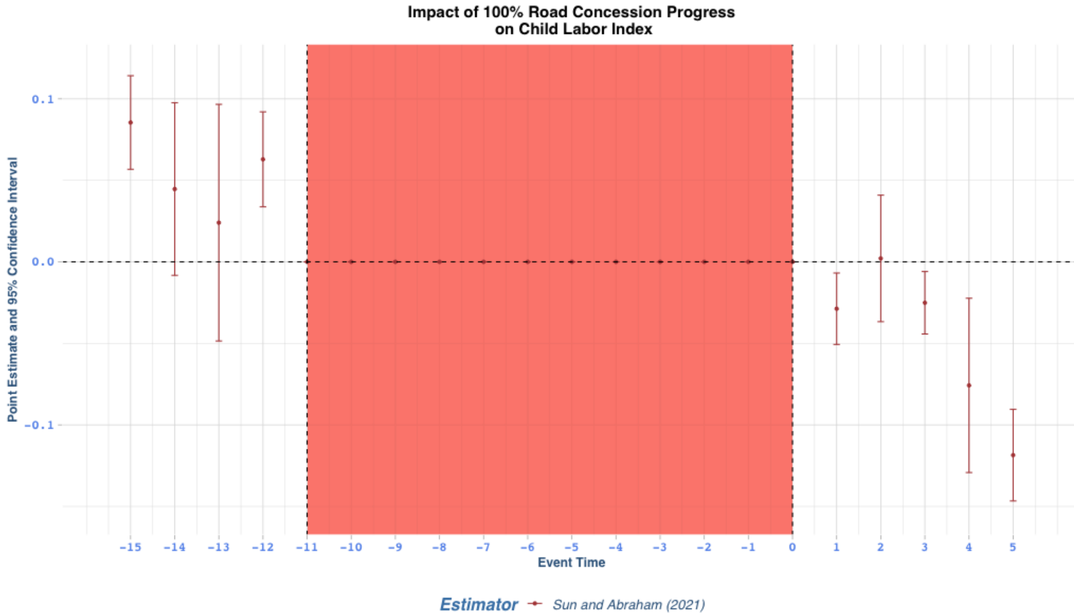

Figure 22: Impact of Road Construction on Child Labor Index (100% Completion). This figure shows the estimated ATT for the Child Labor Index in each year relative to the year when the road project is fully completed. The shaded area indicates the reference periods excluded from the estimation. Error bars represent 95% confidence intervals.

Human Capital Accumulation Index

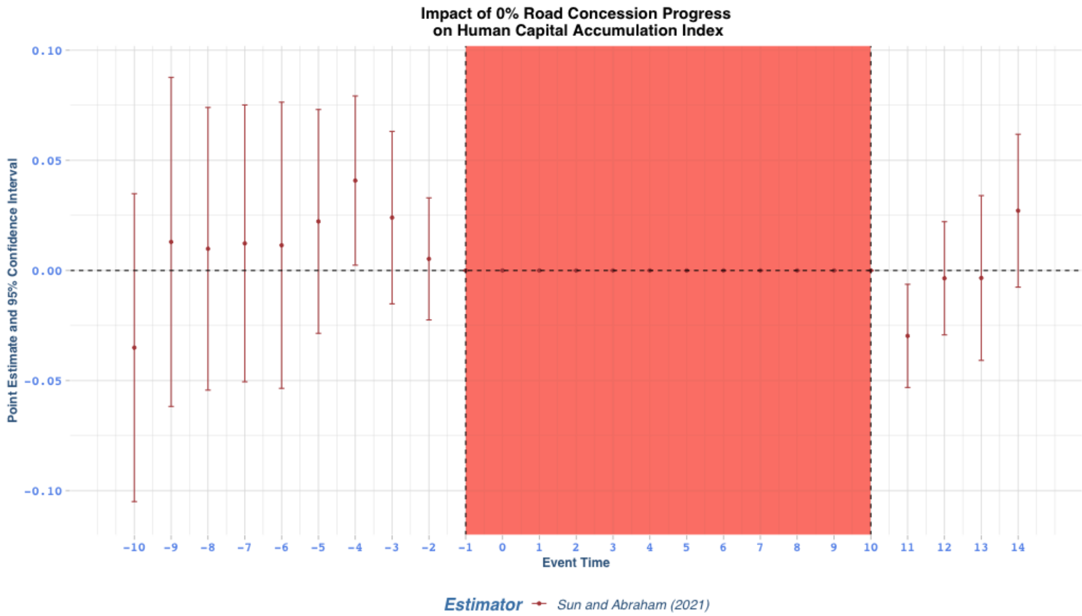

Figure 23: Impact of Road Construction on Human Capital Accumulation Index (0% Completion). This figure shows the estimated ATT for the Index in each year relative to the start of road projects. The shaded area indicates the reference periods excluded from the estimation. Error bars represent 95% confidence intervals.

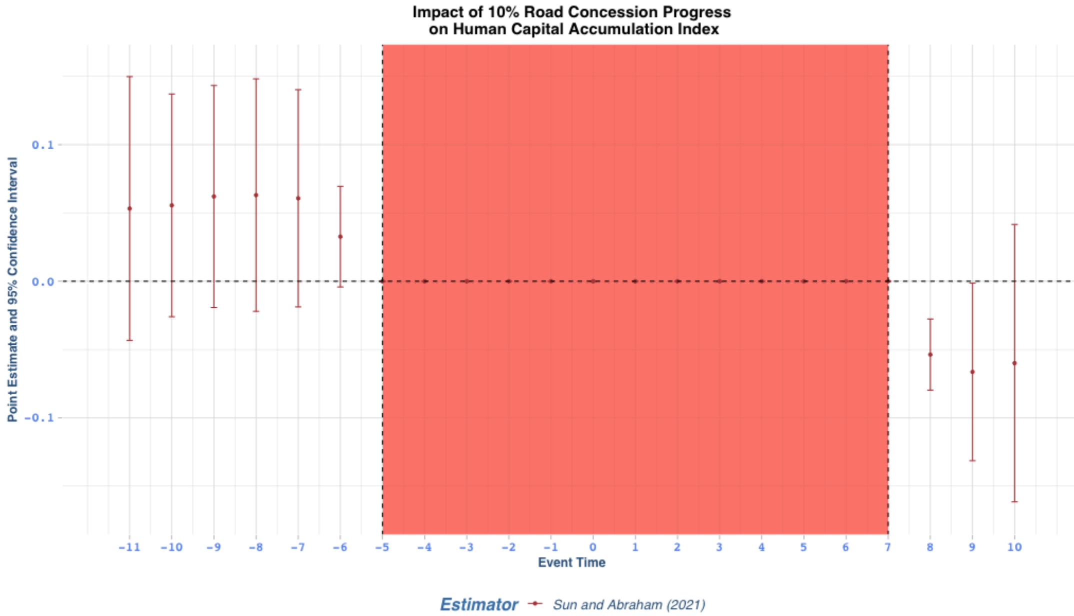

Figure 24: Impact of Road Construction on Human Capital Accumulation Index (10% Completion). This figure shows the estimated ATT for the Index in each year relative to the year when the road project reaches 10% completion. The shaded area indicates the reference periods excluded from the estimation. Error bars represent 95% confidence intervals.

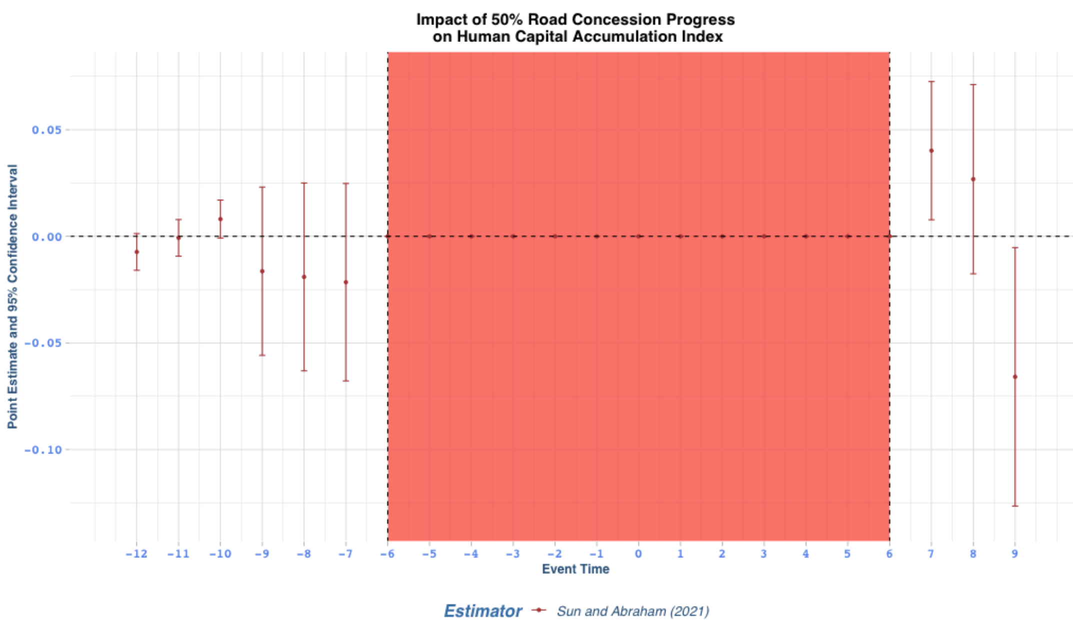

Figure 25: Impact of Road Construction on Human Capital Accumulation Index (50% Completion). This figure shows the estimated ATT for the Index in each year relative to the year when the road project reaches 50% completion. The shaded area indicates the reference periods excluded from the estimation. Error bars represent 95% confidence intervals.

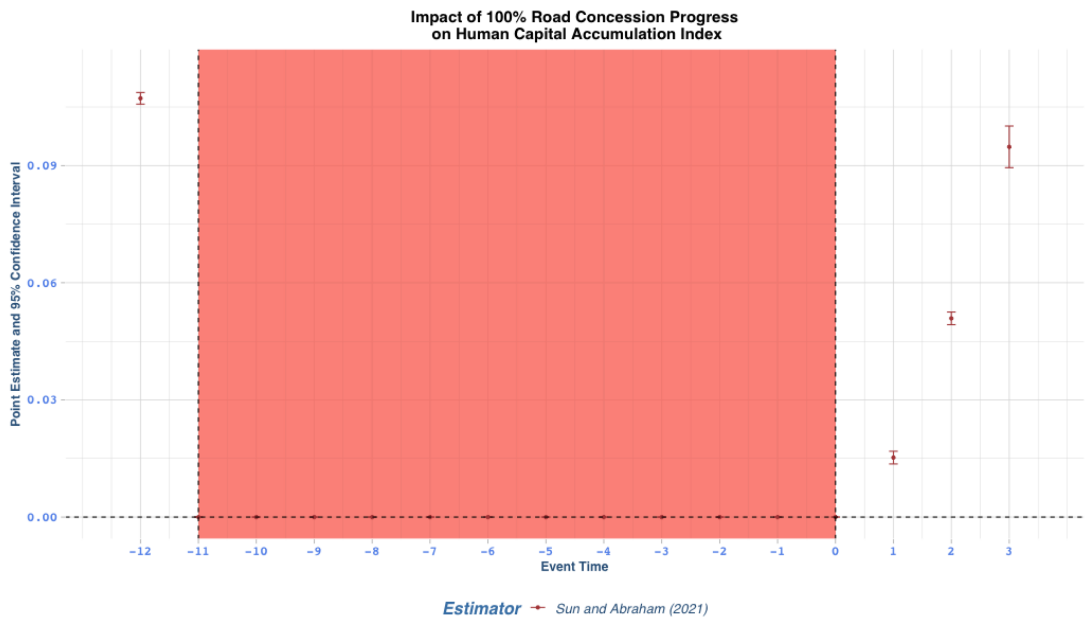

Figure 26: Impact of Road Construction on Human Capital Accumulation Index (100% Completion). This figure shows the estimated ATT for the Index in each year relative to the year when the road project is fully completed. The shaded area indicates the reference periods excluded from the estimation. Error bars represent 95% confidence intervals.

Appendix A.6: Heterogeneity by Distance

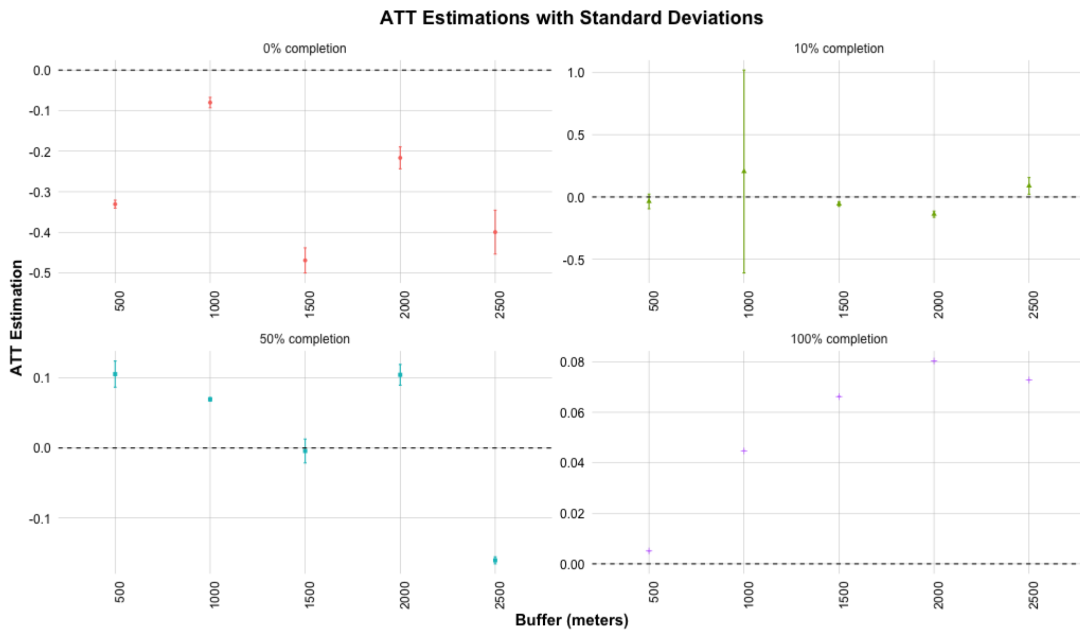

Figure 27: Robustness of ATT Estimations for Math Scores across Distance Bands and Construction Stages, Referencing t-1. Each panel (0%, 10%, 50%, 100% Completion) displays Sun & Abraham (2021) ATT estimates where the primary reference period for identifying the treatment effect is the year immediately preceding the achievement of that specific construction milestone (t-1). The "treatment" event for each panel is defined by reaching that milestone. Error bars represent 95% confidence intervals. Each data point shows the estimated ATT for schools within a specific distance band from the road for that milestone-specific analysis.

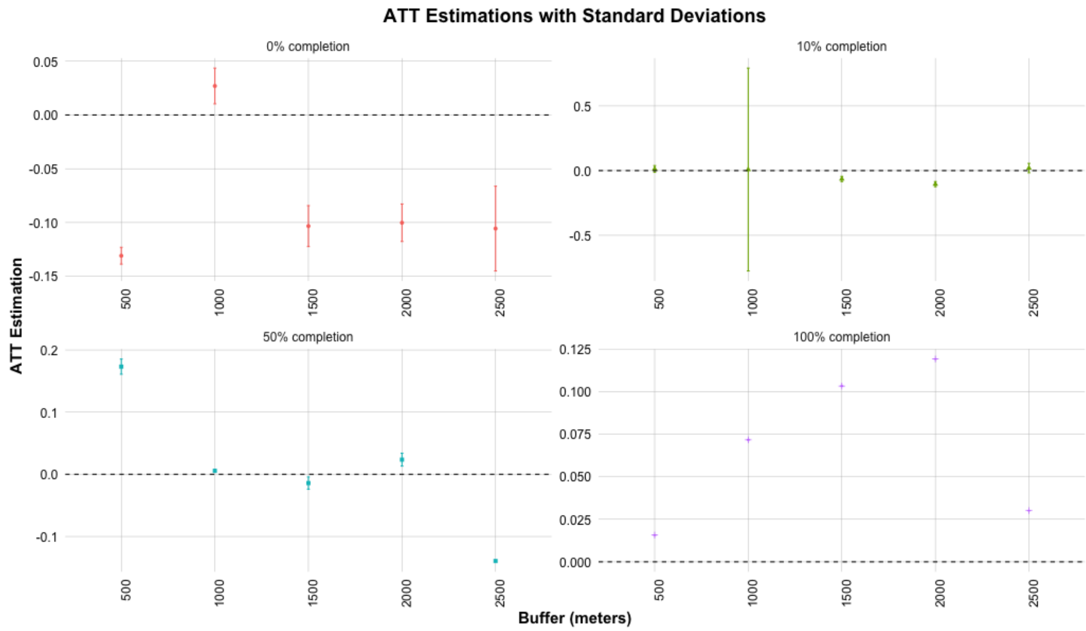

Figure 28: Robustness of ATT Estimations for Reading Literacy Scores across Distance Bands and Construction Stages, Referencing t-1. Each panel (0%, 10%, 50%, 100% Completion) displays Sun & Abraham (2021) ATT estimates where the primary reference period for identifying the treatment effect is the year immediately preceding the achievement of that specific construction milestone (t-1). The "treatment" event for each panel is defined by reaching that milestone. Error bars represent 95% confidence intervals. Each data point shows the estimated ATT for schools within a specific distance band from the road for that milestone-specific analysis.