Hit the Road Jack: High-Quality Roads, Poverty and the Middle Class in Ecuador*

Osmar Bolivar† Gustavo Canavire-Bacarreza‡ Andrew Balthrop§

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Abstract

Road infrastructure plays a crucial role in improving access to essential services, enhancing economic opportunities, and fostering social inclusion, thereby contributing to poverty reduction. This paper assesses the impact of paved major roads on poverty and income mobility in Ecuador's granular regions that gained access to such infrastructure between 2012 and 2019, while also exploring the underlying mechanisms. Using geospatial road data, we track the construction of new primary roads over time, linking this with socioeconomic data from the National Employment, Unemployment, and Underemployment Survey (ENEMDU). We use the max-p-region algorithm to aggregate neighboring parishes to ensure representativeness at a granular geographical level. Through staggered difference-in-differences estimators, we estimate the causal effects of road infrastructure on poverty reduction and income mobility. The results indicate that access to paved roads reduces poverty rates overall, though no significant impact is observed at the extreme poverty level. Both lower-income and middle-income classes experience growth following road access.
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*The opinions expressed in this paper are those of the authors and do not necessarily reflect the views of the World Bank, its Board of Directors, or the countries it represents. All remaining errors are our own.

†Ministry of Economy and Public Finance, La Paz, Bolivia. Email: osmar.economics@gmail.com

‡World Bank, Poverty and Equity Global Practice, Washington DC and Universidad Privada Boliviana, La Paz, Bolivia. Email: gcanavire@worldbank.org

§University of Tennessee, Knoxville, TN, USA, Email: balthrop@utk.edu

1 Introduction

National governments expend substantial resources on transportation infrastructure under the assumption that such expenditures improve economic outcomes. There remains important opportunities for future investment because a significant fraction of rural communities still lie more than 2 km from the nearest all-season road (CIESIN, 2023), while roadway expenditures in developing countries have not kept pace with increasing unit costs (Foster et al., 2022; Collier et al., 2016). The UN estimates that more than 575 million people continue to live in extreme poverty, with lack of road access being an important enough barrier to development that it represents a specific UN Sustainable Development Goal target (9.1.1). Additional rural road construction is therefore expected be an effective strategy to alleviate poverty (Starkey and Hine, 2014).

Yet the relationship between road infrastructure, transportation costs, economic development and poverty is theoretically complex because of inter-connected economic effects involving the movement of inputs, factors and outputs (Redding and Turner, 2015). Well-maintained roads reduce transport costs, resulting in price convergence in these various markets, enhancing economic efficiency. The precise effects on local populations and welfare then depend on the distribution of pre-road prices. In the developing economy context, rural road infrastructure usually entails higher wages and lower prices for rural communities (Asher and Novosad, 2020). Additionally, roads are necessary but insufficient for poverty alleviation because they require access to complementary transportation services (Bryceson et al., 2008). Previous studies have found mixed effects of roads on poverty that are highly dependent on the specific context of the road-building program (Kaiser and Barstow, 2022), warranting country- and program-specific evaluation.

In this study, we assess the impact of paved major roads on poverty alleviation and income mobility in Ecuadorian regions that gained access to such infrastructure between 2012 and 2019. Recognizing the essential role of road infrastructure in expanding access to services, economic opportunities, and social inclusion, we aim to quantify these effects within Ecuador's diverse local contexts. By integrating geospatial data on road construction with socioeconomic data from Ecuador's National Employment, Unemployment, and Underemployment Survey (ENEMDU), we track the socioeconomic impact of primary road networks over time. To ensure accurate representativeness at granular geographical levels, we employ the max-p-region algorithm to aggregate data across neighboring parishes, capturing regional variations effectively. Using staggered difference-in-differences estimators, we estimate the causal effects of road access on poverty and income mobility and identify specific mechanisms driving these outcomes.

We show paved roads reduce poverty rates in Ecuadorian areas generally, but not at the most extreme levels. The poverty rate of those living below \$6.85 per day declines by 13.45 percentage points over the sample period, but there is no change in the rate of people with incomes less than \$2.5 per day. This is consistent with the idea that the poorest households may lack access to transportation services or be otherwise constrained from travel despite road construction. In contrast, lower-income (above poverty line) and middle income classes grow. The mechanisms for poverty reduction is labor income, which increases by 25.7% in treated areas. Labor incomes increase for both men and women, with the most substantial gains accruing to individuals working at medium and large firms in the service sector.

These results are important for a number of reasons. First, while there are causal studies of roadways on poverty in other areas, South America remains comparatively under-studied (Iimi et al. (2015), being the notable exception), with no previous studies specific to Ecuador. South America has unique geographical characteristics and climate features, with both dense rainforest and some of the world's tallest mountains. Ecuador is a microcosm of these features, with coastal plains in the west, a central belt of mountainous terrain, and Amazon rainforest in the east. While the coast and mountain regions are comparatively well-connected, the east is not and is the site of major road building we study. This region is divided by steep ridges, dense forests, and torrential rivers, separating communities into ethnically distinct enclaves, providing a unique treatment context worthy of examination.

Second, our study contributes to a corpus of causal research on road-building and poverty. Similar to previous research, we do not find strong poverty alleviation effects of road-building on the worst-off individuals. Instead benefits accrue primarily through labor income gains to the non-impoverished poor and middle class. However, while previous studies show these gains are driven through manufacturing employment (Spey et al., 2019; Gertler et al., 2024; Hine et al., 2019), it is the service sector that drives income gains in rural Ecuador. Our difference-in-difference identification strategy is methodologically similar to (Aggarwal, 2018; Nakamura et al., 2020; Xie et al., 2023; Charlery et al., 2016; Nguyen et al., 2017; Shamdasani, 2021). While this methodology has been criticized because of the potential for simultaneous confounds with road construction, it has the virtue of allowing for examination of the effect of major connecting roads. In contrast, explicitly randomized road construction of terminal node feeder roads has shown the effect of roads is smaller than the difference-in-difference studies (Asher and Novosad, 2020). Yet new construction of arterial connectors has both larger and more geographically diffuse effects through the simultaneous linking of more economic centers, as opposed to the connection of small villages to existing road networks. Our study provides another piece of evidence that the benefits of secondary roads are substantial.

Our study proceeds as follows. We discuss our methods in section 2. Results are presented in section 3, followed by a short conclusion in section 4.

2 Methodology

We estimate the treatment effect of paved roads by comparing areas of road construction to comparable areas where no major roads were built. This strategy requires careful demarcation of geographical units and the definition of the treatment.

2.1 Geographical Units

Ecuador's administrative geographic divisions include national, province, canton, and parish levels.[1] For this analysis, we adopt a level of aggregation between the canton and parish levels. Specifically, we construct clusters of parishes with similar poverty rates and population characteristics, forming new regions smaller than cantons.

The National Survey of Employment, Unemployment, and Underemployment (ENEMDU) is the primary source of socioeconomic data in Ecuador. However, these surveys only provide representativeness at the national, urban-rural, and provincial levels. This level of geographical disaggregation is insufficient for this study, which aims to assess the impact of paved major roads on poverty and income mobility at a more granular regional level. These regions are defined using the max-p-region algorithm proposed by Duque et al. (2012). This algorithm clusters geographic areas into the maximum possible number of homogeneous regions, subject to the constraint that each region surpasses a predefined threshold for spatially extensive regional attributes. This approach is particularly suitable for regionalization problems where the number of regions is not predetermined.

[1] In Ecuador, cantons are equivalent to municipalities in other countries and are divided into parishes. Parishes are the lowest-ranking territorial division.

We conduct regional clustering to group parishes that exhibit similar poverty rates and population levels based on the 2010 census data. We use the 2010 census because it is a pre-treatment year and provides population indicators rather than sample estimates, enhancing the precision of the regional clustering.[2] This process allowed us to create a sample of sufficiently large regions to be representative.

We apply the max-p-region algorithm to 1,016 parishes in Ecuador, using a spatial weights matrix to express the spatial connectivity between parishes. Poverty rates and population data from the 2010 census are used to measure regional homogeneity. We constrain the algorithm to use a minimum of at least three parishes per max-p region.[3] This process results in the definition of 299 max-p geographical units.[4]

Appendix A provides maps depicting the parishes, the max-p geographical units, and their 2010 census poverty rates.

2.2 Defining Major Roads

Road investments yield the greatest benefits in large-scale projects, particularly those that connect cities or towns to a national road network, facilitating the high mobility of goods and people (Coşar et al., 2022). In Ecuador, the *Red Vial Estatal* is the network of arterial highways and connectors with the highest vehicle traffic volume. It connects provincial capitals, urban centers of cantons, international border ports, and major business areas. Managed by the central government, we refer to these as "major roads" throughout this study.

This study focuses on assessing the impact of paved major roads on poverty and income mobility for the regions that gain access to these roads between 2012 and 2019, by means of a staggered difference-in-differences approach. We take the following steps to integrate the major roads network into our analysis:

1. **Initial Selection:** We begin with the entire network of major roads in Ecuador.
2. **Year of Pavement Completion:** We determine pavement completion year for these roads by segment, as large-scale roads are often paved progressively. This

[2]The 2010 census only includes Unsatisfied Basic Needs (UBN) poverty headcount ratios. Despite this limitation and UBN poverty reflecting structural poverty, this variable was used for the max-p clustering.

[3]Parishes from the Galapagos Islands were excluded because they are not directly connected to the major road network in Ecuador.

[4]As a robustness check, we tested estimates using max-p regions with at least two or four parishes per region. The main findings remained consistent, but regions with at least three parishes are preferred due to lower variance when aggregating data from the individual level to the max-p region level.

characterization is based on administrative reports from Ecuadorian government agencies and remote-sensing analysis of satellite imagery to identify when a road segment transitioned from dirt to pavement.

3. **Labeling for Treatment and Control Units:** Major roads are categorized to distinguish between treated units (i.e., regions that gained access to paved major roads between 2012 and 2019) and never-treated units (i.e., regions that did not gain such access by 2019). Consequently, the network is divided into three categories:
   - ***Roads to Identify Treated Units:*** Major road segments that are paved between 2012 and 2019.
   - ***Roads to Identify Never-Treated Units:*** Major road segments that remain dirt or gravel prior to 2019.
   - ***Roads to Identify Excluded Units:*** Major roads that are paved before 2010.

2.3 Treatment

In alignment with the study's objective, treatment is defined as:

> *"Having access to a paved major road for the first time between 2012 and 2019."*

We follow the methodology of Bolivar (2022) to allocate treatment status by superimposing the major road network onto the polygons of the 299 max-p geographical units. We exclude polygons intersecting with major roads paved prior to 2010 from the analysis; excluding these regions ensures greater comparability between treatment and control regions by removing areas that benefit from road improvements before the study period.

We assign a never-treated status to max-p regions with no intersections with major roads prior to 2019. Conversely, treated units are those where the polygons intersect with major road segments that were paved between 2012 and 2019. In cases where a polygon intersects with several roads paved within this period, the treatment status is assigned based on the earliest pavement completion date.

As a result, 108 of the initial 299 max-p geographical units are selected as units of analysis. Appendix B presents maps illustrating the major roads and geographical units in Ecuador, showing how roads intersect with polygons to determine treatment status over time. We detail the empirical approach in the following section.

2.4 Data and Empirical Strategy

We use 108 max-p regions for our analysis, representing geographical units that either gained access to a paved major road between 2012 and 2019 or did not have such access during the study period. As discussed in Section 2.1, max-p regions are formed by aggregating parishes based on similarities in poverty rates and population indicators, ensuring that each max-p region has a sufficiently large sample size at the individual level. This enables us to confidently use data from the National Survey of Employment, Unemployment, and Underemployment (ENEMDU) and generate representative aggregated indicators for each region.

Using this geographical aggregation, we construct a Repeated Cross-Section (RCS) dataset covering the period from 2010 to 2019 that aggregates individual-level data from Ecuador's ENEMUD. This results in 873 observations derived from 77,090 individual data points. After applying expansion factors, these individual observations represent a total population of 7,530,624.

Table 1 presents the distribution of observations in the RCS dataset over time at the max-p-region level. It also provides information on the number of individual records from the ENEMUD surveys used to construct the dataset. Notably, the years 2014 to 2017 have more observations due to larger household survey samples in these years.

Table 1: Distribution of Observations in the Repeated Cross-Section Dataset

Year	Max-p Region Level			Survey Individual Records	
	Total	Treated	Control	Without Expansion	With Expansion
2010	82	0	82	5,265	681,828
2011	83	0	83	3,908	696,983
2012	84	7	77	4,558	728,267
2013	77	11	66	5,605	756,343
2014	100	12	88	12,846	704,217
2015	95	16	79	12,139	719,571
2016	95	23	72	12,453	755,018
2017	95	30	65	12,205	848,053
2018	81	29	52	4,022	823,674
2019	81	54	27	4,089	816,670
Total	873	182	691	77,090	7,530,624

As previously mentioned, we identify 108 max-p regions; however, the ENEMUD surveys do not consistently cover all these regions each year, resulting in variability in the number of max-p regions in the dataset over time. For example, the maximum number of regions captured in any given year is 100. As shown in Table 1, treatment implementation varies across the study period. Treatment status remains unchanged once a region gains access to a major paved road.

We examine the effect of roads on several measures of poverty and income. First, we use the World Bank's poverty lines of \$2.15, \$3.65, and \$6.85 per day, adjusted to 2017 PPP prices. These correspond to the thresholds for Extreme Poverty, Lower Middle-Income, and Upper Middle-Income countries, respectively. Based on these thresholds, individuals in the Household Surveys are classified as either poor or not poor. Subsequently, for each max-p region i and year t, three poverty headcount ratios are calculated using the 2017-PPP-adjusted poverty lines of \$2.15, \$3.65, and \$6.85 per day.

We also incorporate income mobility indicators. Following the World Bank's definitions, we distinguish between the vulnerable population and the middle class. The vulnerable population consists of individuals who are not classified as poor but are at risk of falling into poverty due to income shocks, with earnings between \$6.85 and \$14 per day (2017 PPP). The middle class, defined as those with lower probabilities of falling into poverty but not considered rich, have earnings between \$14 and \$81 per day (2017 PPP). Using these income thresholds, individuals in the ENEMUD surveys are categorized as either vulnerable or middle class. For each max-p region i and year t, we calculate two additional outcome variables: the percentage of people classified as vulnerable and the percentage classified as middle class. Refer to Appendix C for descriptions and statistics on the outcome variables and other relevant indicators from the RCS dataset, disaggregated by treated and never-treated units of analysis.

Staggered treatment allocation in Table 1 allows us to employ the DiD methodology with multiple time periods, as proposed by Callaway and Sant'Anna (2021), to evaluate the effects of paved major roads on our outcome variables. Within this framework, we adopt a conditional parallel trends assumption, relying on a "never-treated" group of max-p regions that did not receive access to paved roads during the study period, combined with a doubly robust estimator. We incorporate population data from the 2010 Census as a pre-treatment covariate under this assumption to account for regional differences that could influence trends in poverty and income mobility independently of road access. By conditioning on population levels, we reduce potential biases due to underlying demographic and socioeconomic variations across treated and control regions.

This allows for flexible handling of treatment effect heterogeneity across time and groups, which is critical given that regions vary not only in the timing of treatment but also in their exposure to the treatment. Traditional two-way fixed effects (TWFE) models, commonly used in DiD analyses, can suffer from issues such as negative weighting and incorrect aggregation of treatment effects across time and groups.[5] In contrast, the Callaway and Sant'Anna approach directly addresses these issues, allowing for more reliable causal identification while avoiding biases from heterogeneous treatment effects.

Our primary objective is to assess how the impact of paved road access evolves over time. We therefore estimate dynamic treatment effects, which permit us to explore how the treatment effect varies depending on the length of exposure to the treatment. Specifically, we use the group-time average treatment effect ($ATT(g,t)$) parameter, defined for each group g (the time period when the group first receives the treatment) and each time period t.

To estimate these dynamic effects, $\theta_{es}(e)$, we calculate and aggregate the ATT$(g, g+e)$ for each group g and time period t using the following scheme:

$$\theta_{es}(e) = \sum_{g \in \mathcal{G}} \mathbf{1}\{g + e \leq \mathcal{T}\} P(G = g \mid G + e \leq \mathcal{T}) \text{ ATT } (g, g + e) \tag{1}$$

Where:

- $\theta_{es}(e)$ represents the average treatment effect after e periods of exposure to the treatment.
- The term $\mathbf{1}\{g + e \leq \mathcal{T}\}$ ensures that only groups treated for at least e periods are considered.
- $P(G = g \mid G + e \leq \mathcal{T})$ is the weight assigned to each group based on the proportion of units first treated in period g.

This aggregation scheme allows us to track how treatment effects evolve over time, providing insights into the dynamics of road access and its influence on poverty and income mobility. Additionally, by focusing on dynamic effects, we can evaluate whether the benefits of paved roads accumulate over time or if the impact diminishes after the initial period. This approach also mitigates the limitations of traditional event study regressions, which can obscure important dynamics due to aggregation biases.

Lastly, we calculate the overall treatment effect θ^0_{es} by averaging $\theta_{es}(e)$ across all event times. This aggregated treatment effect offers a summary measure of the overall impact of paved major roads, providing a broader perspective on the average influence of road

[5] See Goodman-Bacon (2021) for more discussion on these limitations.

access across all treated units and time periods. The usefulness of the overall treatment effect lies in its ability to condense potentially complex dynamics –such as differences in exposure times and regional heterogeneity– into a single, interpretable estimate.

$$\theta_{es}^{0} = \frac{1}{\mathcal{T}-1}\sum_{e=0}^{\mathcal{T}-2}\theta_{es}(e) \tag{2}$$

3 Results

3.1 Poverty Impacts

The overall treatment effect θ_{es}^{0} provides a comprehensive measure of the average impact of access to paved major roads across all treated regions and time periods. By averaging $\theta_{es}(e)$ over all event times, we obtain a single estimate of how road access has influenced poverty on average. This parameter captures the general effect of the treatment, offering a broad perspective on the intervention's impact without focusing on specific exposure durations.

The overall pre- and post-treatment average treatment effects on poverty headcount ratios, presented in Table 2, offer valuable insights into how access to paved major roads has influenced poverty across different income thresholds.

Table 2: Overall Pre and Post ATT Effects on Poverty Headcount Ratios

Outcome Variable	ATT (θ_{es}^{0})	
	Pre	Post
$2.5 Poverty Line	-0.48	2.02
	(1.09)	(2.70)
$3.65 Poverty Line	-0.72	-10.53***
	(1.48)	(3.46)
$6.85 Poverty Line	0.07	-13.45***
	(1.63)	(3.66)

Note: Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Never-treated units are used as a control group.

For the $2.5 poverty line (extreme poverty), the pre-treatment effect is negative but statistically insignificant, suggesting no significant difference between treated and control groups prior to road access. The ATT remains statistically insignificant in the post-treatment period, indicating that road access has not significantly reduced extreme poverty after treatment.

In contrast, for the \$3.65 poverty line, the pre-treatment ATT is negative but still statistically insignificant. Post-treatment, however, shows a significant reduction in poverty, with an ATT of -10.53, which is statistically significant at the 1% level. This result indicates that, on average, the percentage of people earning less than \$3.65 per day is 10.53 percentage points lower in treated regions compared to never-treated regions. This underscores the impact of road access in reducing poverty for individuals within this poverty grouping, highlighting the role of infrastructure improvements in alleviating poverty.

Similarly, for the \$6.85 poverty line, the pre-treatment effect is statistically insignificant, indicating comparable conditions between treated and control groups before road access. Post-treatment, however, the ATT becomes negative at -13.45, statistically significant at the 1% level. This reduction in poverty for individuals earning below \$6.85 per day reinforces the conclusion that road access improves welfare outcomes for a broader segment of the population.

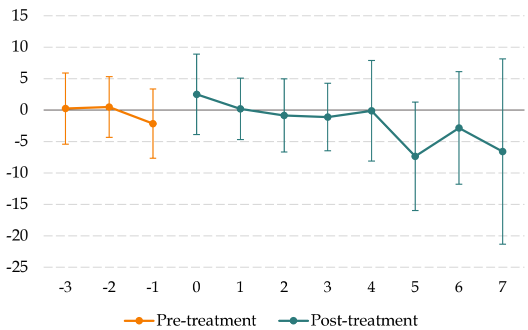
The dynamic effects, shown in Figure 1, along with 95% confidence intervals, allow us to explore the impact of paved roads on poverty across different lengths of exposure to the treatment.

Dynamic effects for the \$2.5 poverty line show no statistically significant reductions in poverty, either pre- or post-treatment, except for a marginal effect in the fifth year post-treatment. The lack of significant effects in both the short and long term suggests that road access may not be sufficient to alleviate extreme poverty or that the benefits take longer to reach the most vulnerable populations.

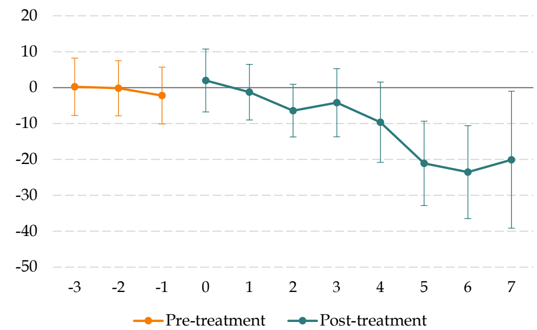
Pre-treatment effects for the \$3.65 poverty line ($t = -3$ to $t = -1$) are statistically insignificant, confirming that treated and control regions exhibit similar poverty trends before road access. At the time of treatment ($t = 0$), the ATT is statistically insignificant, remaining so in $t = 1$ to $t = 3$, indicating no immediate poverty reduction. At $t = 2$, there is a marginally significant reduction in poverty ($ATT = -6.40$, significant at the 10% level). This suggests early signs of poverty reduction. By the fourth year post-treatment and onwards, the effects become more pronounced. The ATT is -9.64 at $t = 4$, , marginally significant at the 10% level; it becomes highly significant at $t = 5$ ($ATT = -21.10$), indicating that infrastructure improvements are generating benefits. Longer-term effects remain significant, with $ATT = -23.53$ at $t = 6$, and $ATT = -20.08$ at $t = 7$, confirming sustained poverty reduction.

Figure 1: Dynamic ATT Effects on Poverty Headcount Ratios

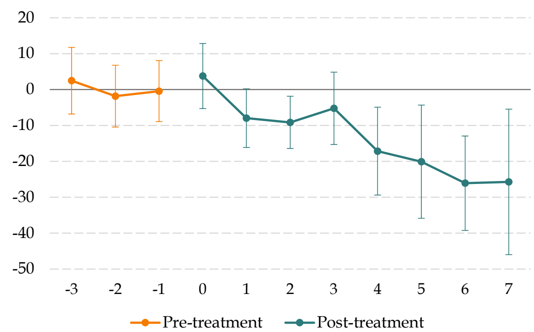
(a) USD 2.5 Poverty Line



(b) USD 3.65 Poverty Line



(c) USD 6.85 Poverty Line



Note: Never-treated units are used as control group. 95% confidence intervals

For the \$6.85 poverty line, the pre-treatment effects are statistically insignificant, confirming parallel trends. The on-impact effect at $t = 0$ is also statistically insignificant. Significant reductions in poverty begin to appear in the short term ($t = 1$ to $t = 3$), with $ATT = -7.96$ at $t = 1$, marginally significant at the 10% level, and $ATT = -9.14$ at $t = 2$, statistically significant. The medium and long-term effects become stronger and more consistently significant, peaking at $t = 6$ ($ATT = -26.08$) and remaining significant at $t = 7$ ($ATT = -25.73$).

3.2 Middle Class Impacts

The overall effects on vulnerable groups, shown in Table 3, reveal that the pre-treatment coefficient is statistically insignificant, suggesting no significant difference between treated and control regions before road paving. However, the post-treatment average shows a statistically significant increase of 9.13 percentage points, implying that access to paved roads has increased the percentage of people classified as vulnerable. This indicates that road access improves incomes, helping individuals transition from poverty to the higher-income “vulnerable” category. The pre-treatment effect shows no significant difference between treated and control regions for the middle class. Post-treatment, the ATT is 4.32 percentage points, statistically significant at the 5% level (Table 3), suggesting that paved roads increased the percentage of people classified as middle class, reflecting enhanced income mobility.

Table 3: Overall Pre and Post ATT Effects on the Percentage of People Classified as Vulnerable and Middle Class

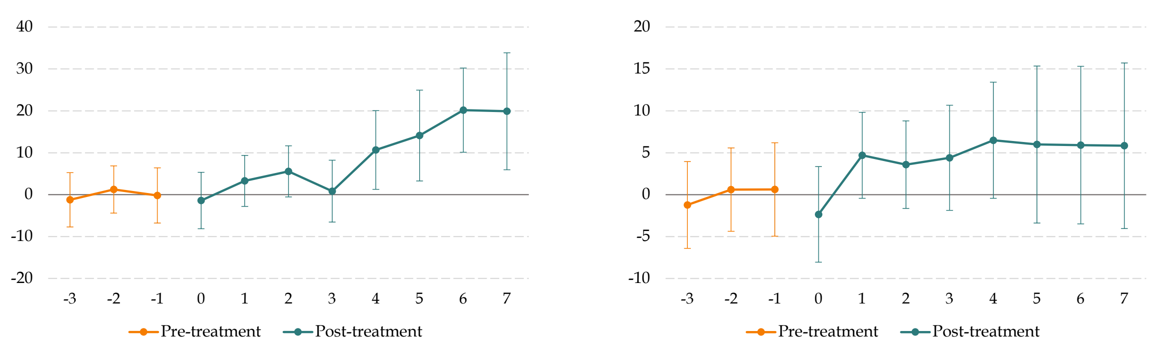
Outcome Variable	ATT (θ_{es}^{0})	
	Pre	Post
Vulnerable	-0.06	9.13***
	(1.27)	(2.79)
Middle Class	0.00	4.32**
	(1.02)	(2.14)

Note: Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Never-treated units are used as the control group.

The dynamic effects for the vulnerable population (Figure 2-(a)), reveal statistically insignificant ATT effects prior to treatment, confirming parallel trends. The on-impact effect shows no immediate effect on the vulnerable population. Effects begin to emerge in the early post-treatment period, with $t = 2$ showing a marginally significant ATT effect of 5.56 percentage points. From the fourth year onward, the effects become significant, peaking at 20.16 percentage points at $t = 6$, demonstrating the accumulation of benefits over time. The effect remains substantial at $t = 7$ (19.89 percentage points).

Figure 2: Dynamic ATT Effects on the Percentage of People Classified as Vulnerable and Middle Class

(a) Vulnerable (b) Middle Class



Note: Never-treated units are used as control group. 95% confidence intervals.

For the middle class (Figure 2-(b)), the dynamic effects prior to treatment are also insignificant, confirming parallel trends. The on-impact effect shows no immediate significant impact. ATT effects begin to appear in the early post-treatment period, with $t = 1$ showing a marginally significant (at the 10% level) effect of 4.69 percentage points. In the medium and long term, effects continue to be positive, peaking at $t = 4$ with a marginally significant effect of 6.49 percentage points, although the later effects remain statistically insignificant.

3.3 Mechanisms

The observed reductions in poverty and improvements in income mobility are driven by significant gains in per capita income, with a notable emphasis on labor income. The treatment effects of access to paved major roads are evaluated using the natural logarithms of per capita overall income and labor income as outcome variables (refer to Appendix C for variable description), capturing percentage changes in these welfare indicators.

As shown in Table 4, the pre-treatment average effect on overall income is statistically insignificant, confirming no meaningful differences in per capita income between treated and control regions before road access. However, the post-treatment ATT effect reveals a 23.5% increase in overall per capita income, statistically significant at the 1% level. This highlights that access to paved roads generates significant and sustained income growth across treated regions after the intervention. The main source of this income growth appears to be labor-market income. The pre-treatment effect on labor income is statistically insignificant, indicating no pre-existing differences between treated and control regions, but the post-treatment ATT effect shows a 25.7% increase in labor income, significant at the 1% level. This suggests that paved roads have significantly improved labor income in treated regions, underscoring the infrastructure's role in fostering economic growth.

Table 4: Overall Pre and Post ATT Effects on Overall and Labor Income

Outcome Variable	ATT (θ^0_{es})	
	Pre	Post
Overall Per Capita Income	-0.4	23.5***
	(2.7)	(6.7)
Labor Per Capita Income	-0.2	25.7***
	(3.0)	(8.0)

Note: Robust standard errors in parentheses. $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$. Never-treated units are used as the control group.

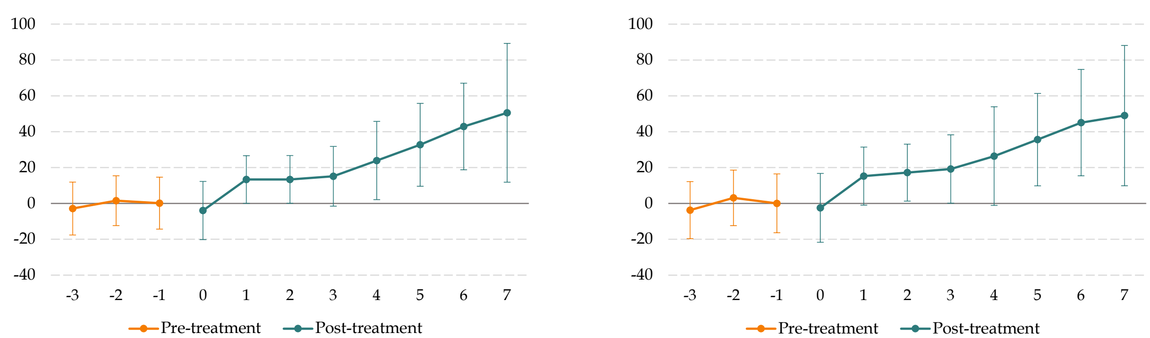
As depicted in Figure 3-(a), the dynamic treatment effects on overall income for the three years prior to treatment ($t = -3$ to $t = -1$) are all statistically insignificant, confirming the validity of the parallel trends assumption and ruling out anticipatory effects. The on-impact effect at $t = 0$ is also insignificant, indicating no immediate change in income upon road access. Starting at $t = 1$, significant positive effects begin to emerge. Overall income rises by 13.3% in the first year post-treatment, significant at the 5% level, indicating that the benefits of road access begin accruing quickly. At $t = 2$, income grows by 13.4%, also significant at the 5% level. By $t = 3$, overall income increases by 15.1%, though this is marginally significant at the 10% level.

The effects become more substantial from $t = 4$ onwards. Overall income increases by 23.9% at $t = 4$, and by $t = 5$, it grows to 32.7%, confirming significant income gains in the medium term. The peak effect is observed at $t = 6$, with a 42.9% increase in overall income, significant at the 1% level. By $t = 7$, the effect remains large at 50.5% and significant, demonstrating the sustained long-term economic impact of road access.

Figure 3: Dynamic ATT Effects on Income

(a) Overall Per Capita Income

(b) Labor Per Capita Income



Note: Never-treated units are used as the control group. 95% confidence intervals.

Labor income effects (Figure 3-(b)) evolve along a similar pathway. Pre-treatment effects from $t = -3$ to $t = -1$ are statistically insignificant, confirming no divergence in labor income trends before treatment. The on-impact effect at $t = 0$ is also insignificant, indicating no immediate short-term impact on labor income following road completion; however, in the early post-treatment period ($t = 1$ to $t = 3$), labor income begins to rise. At $t = 1$, there is a marginally significant effect of 15.3%, and by $t = 2$, the ATT increases to 17.2%, significant at the 5% level, indicating that the effects of road access are starting to take hold. By $t = 3$, the effect reaches 19.2%, also significant at the 5% level. Labor income gains become more pronounced in the medium term: 26.4% at $t = 4$, significant at the 10% level, and 35.6% at $t = 4$, significant at the 1% level. In the long term, the effects peak at $t = 6$, with a 45.1% increase in labor income, significant at the 1% level. Even at $t = 7$, the effect remains substantial at 49.0%, significant at the 5% level, confirming the sustained positive impact of road access on labor income over time.

The RCS dataset, constructed by aggregating individual-level household survey data at the max-p region level, offers an insightful platform to analyze treatment effects on labor income, a key mechanism driving income mobility in regions with paved major roads. To deepen this analysis, we examine labor income effects across specific population subsets, where individuals are categorized based on characteristics such as employment type or sector. These subsets are created by first selecting individuals with a specific characteristic (e.g., self-employed individuals) and then calculating the average labor income for each max-p region and year. These subsets allow us to explore whether the observed gains in labor income are concentrated within particular groups, thereby providing more granular insights into the distribution of road infrastructure benefits. The overall and dynamic ATT effects on labor income by subset are presented in Table 5.

Table 5: Dynamic ATT Effects on Labor Income by Subsets

ATT	Self Employed	Small Firm	Med-Large Firm	Formal Sector	Informal Sector	Primary Sector	Secondary Sector	Service Sector	Men	Women
Pre	-1.4	0.1	-4.3	-0.7	1.7	0.3	6.8	0.6	-0.9	1.0
	(3.4)	(3.1)	(4.5)	(3.8)	(3.4)	(3.7)	(7.2)	(3.4)	(3.1)	(3.2)
Post	25.6**	19.1**	42.4***	25.3**	18.4**	17.0*	-5.5	18.7*	28.3***	23.9***
	(10.4)	(9.2)	(11.3)	(12.5)	(9.0)	(9.2)	(17.9)	(10.4)	(8.1)	(8.3)
$t = -3$	-6.0	-5.6	4.5	-7.1	0.8	-5.9	-5.9	0.5	-4.8	-2.7
	(9.5)	(8.8)	(11.2)	(9.1)	(9.2)	(10.4)	(18.7)	(7.7)	(8.3)	(8.4)
$t = -2$	2.5	5.2	-12.5	11.5	1.3	-0.2	1.7	3.2	2.7	3.8
	(8.5)	(8.1)	(10.9)	(9.1)	(8.2)	(8.7)	(16.6)	(7.6)	(8.0)	(8.1)
$t = -1$	-0.8	0.7	-4.8	-6.5	3.1	7.0	24.8	-1.7	-0.7	2.0
	(8.9)	(8.3)	(12.6)	(10.5)	(8.6)	(9.0)	(17.4)	(9.2)	(8.6)	(8.8)
$t = 0$	-5.4	-6.6	11.9	-3.5	-5.8	-16.1	-25.5	-2.0	-0.5	-5.4
	(10.0)	(9.5)	(15.4)	(12.6)	(10.4)	(10.9)	(16.0)	(9.2)	(10.0)	(10.0)
$t = 1$	15.5*	10.6	31.7***	11.1	11.2	7.8	-25.1	14.3*	16.7*	14.0*
	(9.1)	(8.7)	(10.5)	(10.8)	(9.9)	(10.0)	(22.7)	(8.4)	(8.9)	(8.4)
$t = 2$	13.9	10.9	26.2**	12.6	11.8	4.3	-70.4	21.2**	20.6**	15.8*
	(10.0)	(8.8)	(11.5)	(11.4)	(9.5)	(9.2)	(51.6)	(9.0)	(8.3)	(8.5)
$t = 3$	12.3	5.8	58.5***	22.4*	7.0	4.4	2.9	22.2	20.4**	17.6
	(12.4)	(11.7)	(14.7)	(13.5)	(12.9)	(11.4)	(23.4)	(13.9)	(9.3)	(10.9)
$t = 4$	35.2**	25.0*	28.2	29.2	26.8*	23.2	15.2	30.9*	31.1**	19.8
	(17.9)	(14.4)	(20.7)	(19.0)	(14.4)	(14.6)	(27.5)	(16.3)	(13.3)	(15.6)
$t = 5$	48.0***	33.3**	36.7	33.0	31.7**	23.6	-7.5	20.6	41.8***	32.2**
	(16.6)	(15.2)	(22.4)	(22.1)	(15.7)	(15.6)	(32.2)	(15.5)	(13.7)	(13.6)
$t = 6$	30.0	28.1*	71.6***	30.6	31.9*	40.6***	78.0*	14.5	47.6***	45.5***
	(19.7)	(16.2)	(24.1)	(25.0)	(18.8)	(15.4)	(41.3)	(23.3)	(14.6)	(17.2)
$t = 7$	55.6**	46.1**	74.4***	66.7**	32.3	48.1**	-11.6	28.2	48.4**	51.9**
	(24.3)	(21.4)	(25.3)	(29.0)	(21.8)	(20.9)	(29.7)	(25.9)	(19.5)	(21.7)

Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Never-treated units are used as a control group.

Table 5 demonstrates that pre-treatment effects are statistically insignificant for all groups, providing corroboratory evidence in support of the parallel trends assumption. All groups saw statistically significant increases in labor income post-treatment with the exception of individuals working in the secondary sector (manufacturing). Labor income increases for individuals working in the primary sector (agriculture) were marginally significant. Workers in the service sector experience wage gains of 18.7% post-treatment (significant at the 10% level), underscoring the importance of road access in boosting wages in service-oriented industries. The most pronounced gains are observed in medium-large firms, with a post-treatment ATT of 42.4%, significant at the 1% level. These firms likely capitalize on economies of scale facilitated by better infrastructure, leading to greater wage growth for their employees. Additionally, gender-disaggregated results show significant labor income gains for both men and women. Post-treatment, men's labor income increases by 28.3%, and women's income by 23.9%, both statistically significant at the 1% level. Although men experience slightly higher gains, both genders benefit substantially from improved road access.

The dynamic effects further illuminate these patterns. For self-employed individuals, significant income effects emerge from $t = 1$ and peak at $t = 7$, with a 55.6% increase in labor income. Similar trends are observed for small firms, medium-large firms, and formal and informal sector workers, with medium-large firms showing the strongest dynamic effects, peaking at $t = 7$ with a 74.4% increase in labor income. Gender dynamics also indicate sustained and growing income effects over time, with both men and women experiencing significant income increases in the later post-treatment periods.

Overall, these results confirm that access to paved major roads leads to substantial and sustained improvements in labor income across various population subsets. The most pronounced effects are observed in medium-large firms and formal sector employment, while self-employed individuals and informal workers also experience notable benefits. These findings emphasize the broad-based economic benefits of road infrastructure, particularly in fostering labor income growth and income mobility.

3.4 Robustness

3.4.1 Does the Poverty Definition Matter?

Our primary findings demonstrate that access to paved major roads significantly reduces poverty when considering the World Bank's poverty lines of \$3.65 and \$6.85 per day (adjusted to 2017 PPP prices). To ensure the robustness of these results, we evaluate whether the observed impacts on poverty persist when using alternative poverty definitions, specifically Ecuador's official moderate and extreme poverty headcount ratios. This allows us to assess whether the choice of poverty line alters the conclusions regarding the impact of road access on poverty reduction.

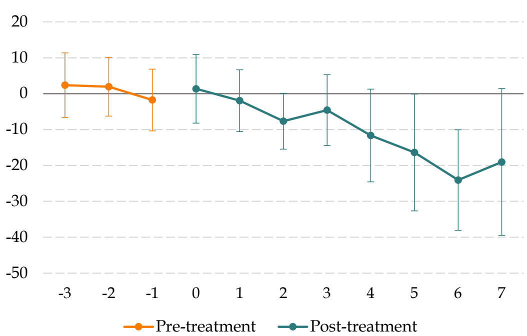
Table 6: Overall Pre and Post ATT Effects on Ecuador's Official Poverty Headcount Ratios

Outcome Variable	ATT (θ^0_{es})	
	Pre	Post
Moderate Poverty Line	0.84	-10.50**
	(1.68)	(4.09)
Extreme Poverty Line	-0.85	-5.70*
	(1.31)	(3.10)

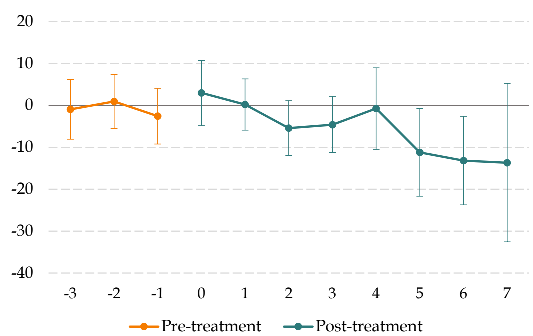
Note: Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Never-treated units are used as a control group.

Figure 4: Dynamic ATT Effects on Ecuador's Official Poverty Headcount Ratios

(a) Official Moderate Poverty Line



(b) Official Extreme Poverty Line



Note: Never-treated units are used as control group. 95% confidence intervals.

Table 6 presents the overall average treatment effects using Ecuador's official poverty indicators. The pre-treatment effects remain statistically insignificant for both moderate and extreme poverty, confirming that prior to road access, there were no significant differences in poverty trends between treated and control regions. This supports the validity of the parallel trends assumption. However, post-treatment effects are significant, with a reduction of -10.50 percentage points in moderate poverty, statistically significant at the 5% level. Similarly, extreme poverty decreases by -5.70 percentage points, marginally significant at the 10% level. These results confirm that the infrastructure improvements, when measured using national poverty definitions, still generate poverty reductions in the treated regions. The findings reinforce the conclusion that road access has a positive impact on poverty alleviation, regardless of the specific poverty definition used.

Dynamic effects further confirm the robustness of these findings. As shown in Figure 4, there are no significant changes in poverty prior to road access, indicating parallel trends. The post-treatment period reveals a significant and sustained reduction in both moderate and extreme poverty from year four onward, aligning with the effects observed using the World Bank poverty lines. This consistency across different poverty definitions underscores the robustness of the results.

3.4.2 Never-treated vs. Not-yet-treated

The DiD methodology employed in this study relies on the use of a "never-treated" group of max-p regions as the control group, ensuring the validity of the parallel trends assumption. To further assess the robustness of our findings, we estimate the treatment effects using an alternative control group composed of "not-yet-treated" regions—those that will receive road access in later periods but have not yet been treated. This provides an additional test of the parallel trends assumption and the robustness of the estimated ATT effects.

Table 7 presents the overall average treatment effects when using not-yet-treated units as the control group. The results remain consistent with those obtained using the never-treated control group. For the \$2.5 poverty line, the effects are negative but statistically insignificant, suggesting limited impact on extreme poverty when using this threshold. However, for the \$3.65 and \$6.85 poverty lines, the post-treatment effects are highly significant, showing reductions of -9.97 and -12.48 percentage points, respectively, both significant at the 1% level. These results align closely with our original findings, confirming the robustness of the treatment effects.

In addition to poverty, we also examine the effects on vulnerability and the middle class. The post-treatment effect on the percentage of people classified as vulnerable is positive and statistically significant at the 1% level, with an ATT of 9.23 percentage points. This mirrors the results obtained using never-treated regions as the control group and reinforces the robustness of the interpretation that road infrastructure contributes to improving economic conditions for lower-income populations. For the middle class, the post-treatment effect is positive but statistically insignificant when using not-yet-treated units as the control group, with an ATT of 3.25 percentage points. This result contrasts

Table 7: Overall Pre and Post ATT Effects With Not-Yet-Treated as Control Group

Outcome Variable	ATT (θ^0_{es})	
	Pre	Post
\$2.5 Poverty Line	-0.53	-2.24
	(1.12)	(2.60)
\$3.65 Poverty Line	-0.83	-9.97***
	(1.52)	(3.40)
\$6.85 Poverty Line	0.19	-12.48***
	(1.68)	(3.54)
Vulnerable	-0.05	9.23***
	(1.29)	(2.74)
Middle Class	-0.14	3.25
	(1.04)	(2.09)

Note: Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Not-yet-treated units are used as a control group.

slightly with the findings using never-treated units, where the post-treatment effect on the middle class was statistically significant. Despite the lack of significance in the not-yet-treated analysis, the positive ATT suggests a consistent direction in the effect, implying that paved road access has the potential to expand the middle class over time.

Appendix D provides further analysis of the dynamic effects, showing that the results are robust when using not-yet-treated units as the control group. Both poverty reduction and income mobility effects follow a similar pattern to those estimated using never-treated regions, providing additional confidence in the reliability of the estimated impacts of road access on poverty and income dynamics. The observed increase in vulnerability and the positive, albeit not statistically significant, effect on the middle class are consistent with the broader findings that road access improves welfare by lifting people out of poverty and enabling upward mobility.

3.4.3 Conditional vs. Unconditional Parallel Trends

To further assess the robustness of our findings, we compare the effects under both conditional and unconditional parallel trends assumptions. Table 8 demonstrates that the impact of paved major roads on poverty reduction and income mobility remains consistent under the unconditional parallel trends assumption. Specifically, the ATT estimates are statistically significant for poverty lines at \$3.65 and \$6.85, as well as for the vulnerable and middle-class groups. The post-treatment effect magnitudes and directions align closely with our primary results, reinforcing the robustness of the findings in Section 3.

Table 8: Overall Pre and Post ATT Effects Under Unconditional Parallel Trends Assumption

Outcome Variable	ATT (θ^0_{es})	
	Pre	Post
\$2.5 Poverty Line	-0.40	-1.70
	(1.07)	(2.89)
\$3.65 Poverty Line	-0.50	-10.05***
	(1.51)	(3.72)
\$6.85 Poverty Line	0.28	-12.72***
	(1.64)	(3.76)
Vulnerable	-0.21	8.62***
	(1.25)	(2.93)
Middle Class	-0.07	4.10*
	(1.03)	(2.15)

Note: Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Never-treated units are used as a control group.

The dynamic effects analysis under the unconditional parallel trends assumption, presented in Appendix E, further confirms the robustness of our main results across time.

These robustness checks confirm that our main results are stable across both assumptions, supporting the validity of the observed effects. Nonetheless, the conditional parallel trends assumption, by controlling for baseline population differences, yields narrower confidence intervals and more precise estimates, making it the preferred approach for our primary analysis.

3.4.4 Placebo Test

To reinforce the robustness of our findings, we implement two placebo tests designed to assess the stability of results in the absence of actual treatment effects.

- **Temporal Shift of Treatment (Placebo 1):** In this placebo test, we use only pre-2012 data and assign hypothetical treatment years within the pre-treatment period, ignoring all post-treatment data. Specifically, we select 2007 and 2008 as pseudo-baseline years, while 2009 to 2011 serve as placebo treatment periods. For regions that originally received road access between 2012 and 2013, 2009 is designated as the placebo first-treatment year; similarly, 2010 and 2011 are used for regions treated between 2015–2016 and 2017–2019, respectively.[6] This design main-

[6] No regions were originally treated in 2014.

tains a proportional distribution of treated units across the placebo period, allowing us to test whether any spurious effects arise purely from a temporal reassignment of treatment.

- **Random Treatment Reassignment (Placebo 2):** This placebo test retains actual outcome values but randomizes treatment assignment among units. Specifically, 2/3 of max-p regions are randomly selected as treated units, while the remaining 1/3 are designated as never-treated. First-treatment years are then randomly assigned within the 2012–2019 range for the pseudo-treated units. This test evaluates the possibility of observed effects arising from random treatment allocation rather than genuine road access.

The results for both placebo tests are displayed in Table 9. Consistent with expectations for valid placebo tests, neither placebo demonstrates statistically significant effects in pre-treatment or post-treatment periods across most outcome variables.

Table 9: Overall Pre and Post ATT Effects by Placebo Test

Outcome Variable	Placebo 1		Placebo 2	
	Pre	Post	Pre	Post
$2.5 Poverty Line	-1.80	-2.73	-0.67	1.67
	(2.64)	(4.15)	(0.99)	(2.55)
$3.65 Poverty Line	-0.70	-5.27	0.37	4.98
	(3.15)	(5.03)	(1.50)	(4.17)
$6.85 Poverty Line	-1.97	-4.74	-0.38	7.67
	(2.69)	(4.15)	(1.58)	(4.71)
Vulnerable	2.90	4.01	-1.07	-1.93
	(1.90)	(3.23)	(1.09)	(3.41)
Middle Class	-0.90	0.46	1.45	-5.74**
	(1.56)	(2.17)	(0.89)	(2.58)

Note: Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Never-treated units are used as a control group.

For Placebo 1, both pre- and post-treatment ATT estimates are consistently statistically insignificant across poverty lines ($2.5, $3.65, and $6.85) and for the proportions of the population classified as vulnerable or middle class. The absence of significant effects in this placebo confirms that temporally shifting the treatment period does not yield spurious results, thereby reinforcing the causal interpretation of the main findings.

In Placebo 2, where treatment assignment is randomized, the results similarly show no statistically significant effects across most outcomes. The only exception is a post-treatment effect for the middle class (-5.74), which is significant at the 5% level. While this isolated effect suggests minor variability, it does not challenge the overall robustness of the main findings, as no consistent spurious effects are observed across other outcomes or placebo tests.

Overall, the results from both placebo tests underscore the reliability of the estimated causal effects in the main analysis, with no systematic spurious effects emerging from these alternative testing scenarios.

4 Conclusions

Well-maintained roads facilitate the movement of goods and people, promoting economic development through the more efficient distribution and allocation of resources. Can roads also be a tool for the eradication of extreme poverty? In Ecuador, at least, our results paint a mixed picture. While poverty headcounts are reduced in some poverty categories as a result of road construction, we do not find evidence that access to roads moved people out of the most extreme category of poverty. The building program did, however, improve outcomes in nearly every other category examined: middle class income categories expanded, while labor incomes increased for most groups, including self-employed, those working in the informal and formal sectors, and for those in the primary and tertiary sectors.

These results corroborate previous findings while offering new insights. Previous research has also found that the worst off individuals do not benefit from roads (Asher and Novosad, 2020; Spey et al., 2019; Hine et al., 2019; Gachassin et al., 2010). An important consideration is in making sure those in extreme poverty have adequate access to complementary transportation services. Yet even this may prove insufficient. Many of the poorest households in Ecuador rely on subsistence agriculture, so that we would not expect to see non-farm income gains (or even measurable income). Nonetheless, access to both better and lower-priced inputs, when combined with agricultural extension activities has been show to raise living standards for these types of households(Gebresilasse, 2023). Additionally, lowered output prices as a result of roads may provide welfare improvements (e.g., Aggarwal (2018)). This is a useful area for future research.

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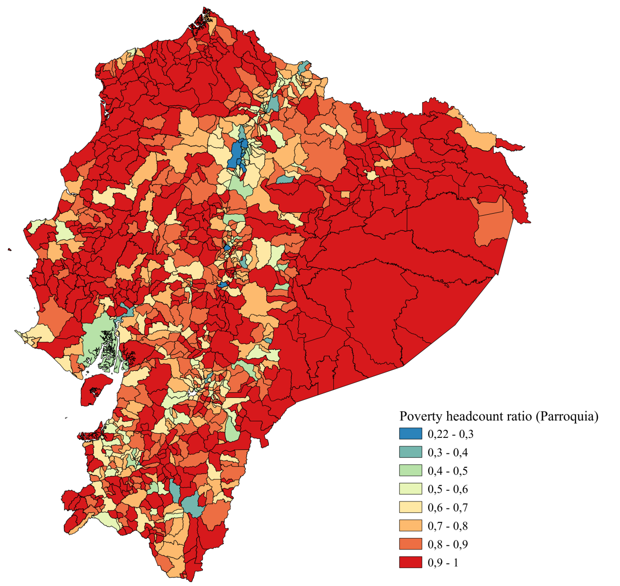
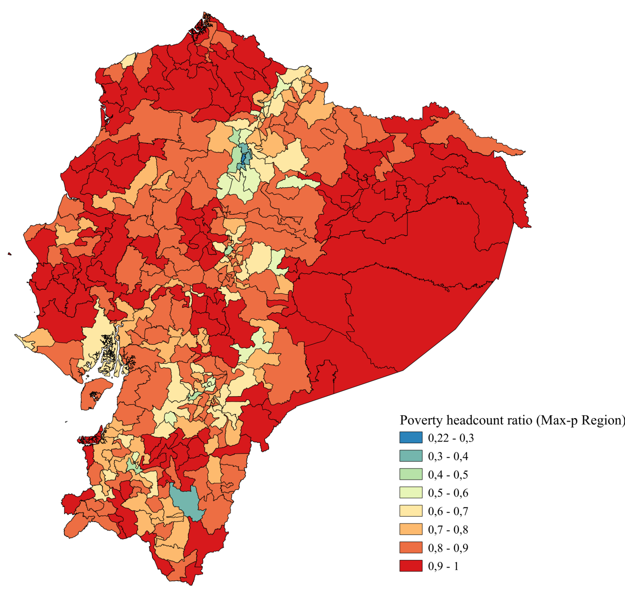
A Maps of 2010 Census Poverty Headcount Ratios by Parishes and Max-p Regions

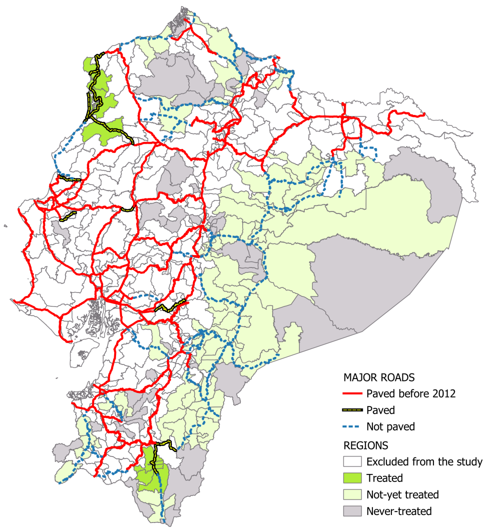


(a) Parish Level

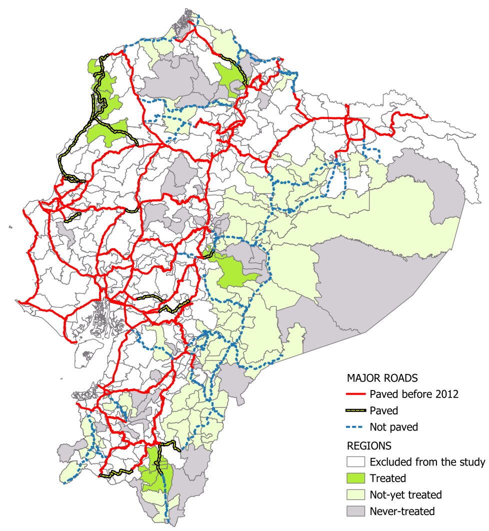


(b) Max-p Regions

B Maps of Treatment Allocation Over Time



(a) 2012



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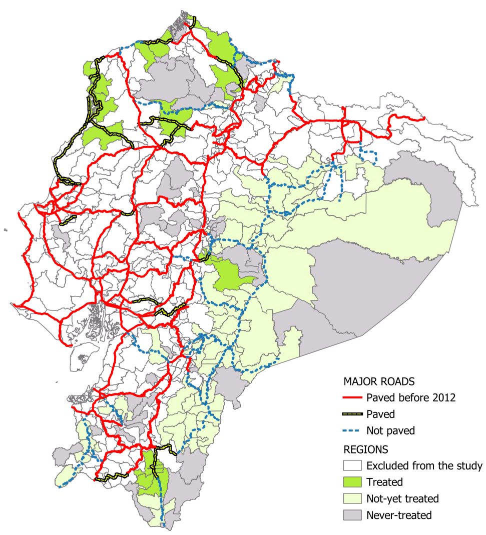

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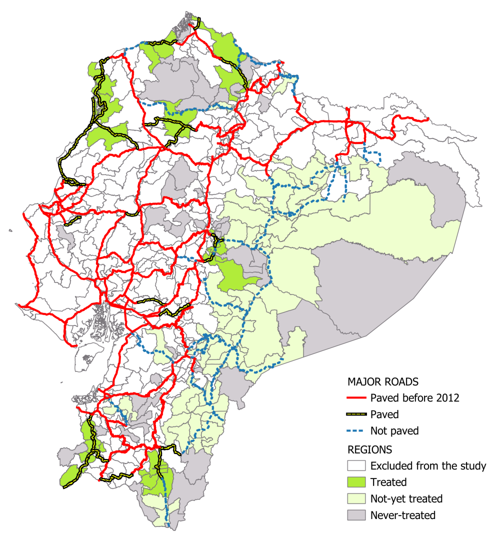
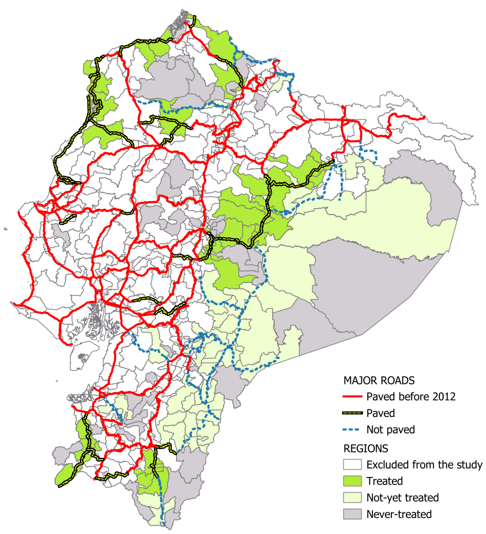
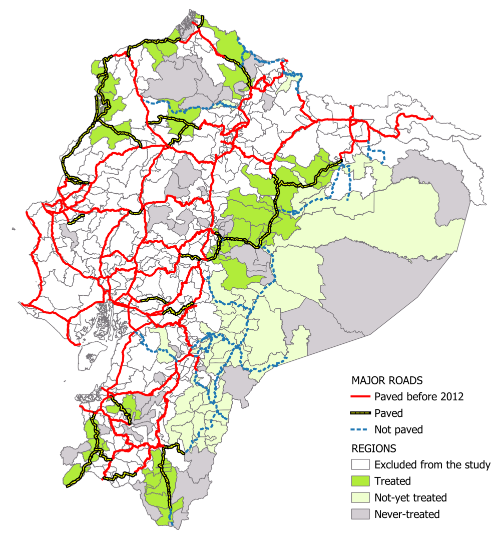


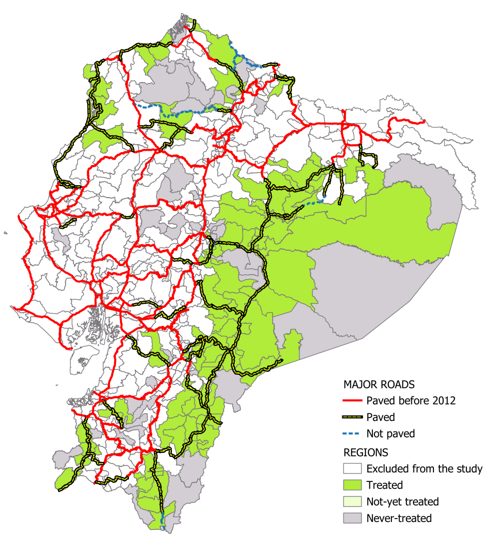
(d) 2016



(a) 2017



(b) 2018



(c) 2019

C RCS Dataset: Variable Description and Statistics

We identified 108 max-p regions for our analysis, representing geographical units that either gained access to a paved major road between 2012 and 2019 or did not receive such access during the study period. A Repeated Cross-Section (RCS) dataset was constructed covering the years 2010 to 2019, aggregating individual-level data from Ecuador's ENEMUD surveys to generate region-level indicators.

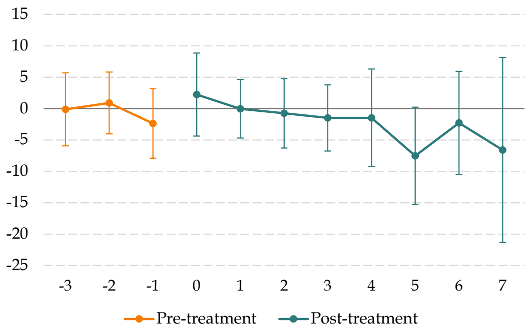
Table 10 presents the mean values of key outcome variables and other indicators from the RCS dataset, disaggregated by treated and never-treated units over time. For example, in 2019, the average poverty headcount ratio (at $3.65 per day) was 25.2% in treated regions, compared to 35.4% in never-treated regions. The following descriptions provide an overview of the variables listed in Table 10:

- **Poverty ($2.5 per day):** Percentage of the population living below the $2.5 per day (adjusted to 2017 PPP prices) poverty line, for max-p region i and year t.
- **Poverty ($3.65 per day):** Percentage of the population living below the $3.65 per day (adjusted to 2017 PPP prices) poverty line, for max-p region i and year t.
- **Poverty ($6.85 per day):** Percentage of the population living below the $6.85 per day (adjusted to 2017 PPP prices) poverty line, for max-p region i and year t.
- **Vulnerable (%):** Percentage of the population earning between $6.85 and $14 per day (adjusted to 2017 PPP prices), for max-p region i and year t.
- **Middle Class (%):** Percentage of the population earning between $14 and $81 per day (adjusted to 2017 PPP prices), for max-p region i and year t.
- **Overall Income ($):** Average per capita overall income for region i and year t.
- **Labor Income ($):** Average per capita labor income for region i and year t.
- **Formal Employment (%):** Percentage of the employed population with formal employment (i.e., with social security) for max-p region i and year t.
- **Years of Education:** Average years of education for region i and year t.
- **Primary Sector (%):** Percentage of the employed population working in the primary sector, for max-p region i and year t.
- **Self-Employment (%):** Percentage of the employed population in self-employment, for max-p region i and year t.
- **Small Firms (%):** Percentage of the employed population working in small firms, for max-p region i and year t.

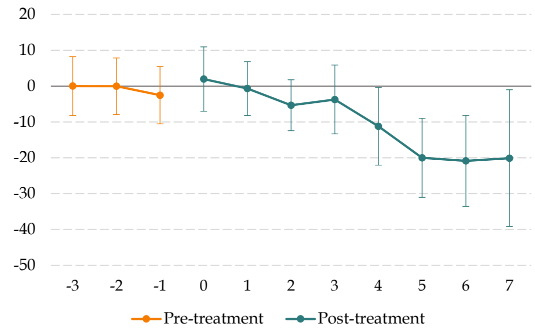
Table 10: Mean Values of Key Variables by Group and Year

Variable	Group	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Avg.
Poverty ($2.5 per day)	Control	13.0	12.7	11.3	8.5	11.2	11.5	14.8	11.6	11.1	15.5	11.9
	Treated			12.4	7.8	12.2	10.3	9.4	10.4	7.9	12.1	10.4
Poverty ($3.65 per day)	Control	33.6	36.1	32.0	22.6	25.6	26.1	31.0	25.5	26.5	35.4	29.3
	Treated			41.4	33.1	28.1	28.2	26.6	24.6	20.0	25.2	26.0
Poverty ($6.85 per day)	Control	64.8	65.5	61.6	53.6	53.8	56.0	57.8	55.4	55.4	62.9	58.7
	Treated			78.1	65.3	59.6	61.7	57.9	51.9	46.5	51.8	54.9
Vulnerable (%)	Control	23.5	23.6	27.4	30.6	30.0	29.8	29.5	27.1	29.8	26.0	27.7
	Treated			15.2	25.7	26.8	26.7	30.4	31.1	34.1	32.5	30.3
Middle Class (%)	Control	11.7	10.9	11.0	15.8	16.2	14.1	12.7	17.5	14.8	11.1	13.6
	Treated			6.6	9.0	13.6	11.6	11.6	17.1	19.4	15.7	14.7
Overall Income ($)	Control	99.7	103.6	113.1	131.9	137.7	134.0	129.6	141.4	137.7	120.3	124.2
	Treated			86.5	108.6	124.1	125.4	128.2	145.1	154.6	142.9	136.2
Labor Income ($)	Control	87.8	91.8	103.7	117.7	124.0	117.5	112.3	120.7	115.6	95.8	109.0
	Treated			78.8	96.0	112.2	111.6	116.2	125.7	135.4	119.6	118.5
Formal Employment (%)	Control	29.8	34.4	33.7	39.1	36.4	33.7	33.7	31.6	26.1	29.8	33.3
	Treated			33.9	38.0	43.3	46.6	44.1	40.1	37.9	34.1	38.9
Years of Education	Control	7.5	7.3	7.5	8.2	8.6	8.7	8.8	8.7	8.4	8.0	8.1
	Treated			6.4	7.7	8.0	7.9	8.3	8.5	8.4	8.8	8.3
Primary Sector (%)	Control	64.1	65.6	64.3	62.3	60.1	62.0	63.5	61.5	63.3	73.6	63.4
	Treated			79.3	58.0	58.0	61.5	59.4	59.7	61.9	63.5	61.8
Self-Employment (%)	Control	40.7	43.0	41.7	38.8	39.8	40.3	40.8	41.1	43.6	43.6	41.1
	Treated			43.4	42.4	41.7	35.3	40.4	38.4	39.5	40.3	39.8
Small Firms (%)	Control	80.1	82.1	81.7	78.9	78.9	79.0	77.4	80.6	79.9	84.8	80.1
	Treated			82.9	87.1	81.8	78.8	80.2	79.9	83.9	81.7	81.7

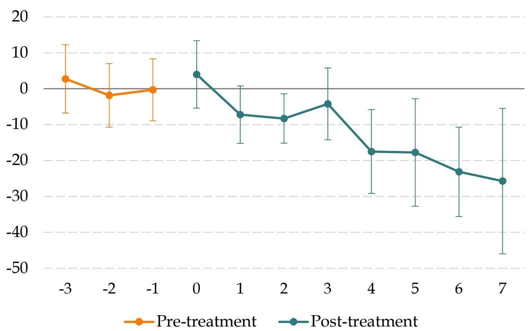
D Dynamic ATT Effects Using Not-Yet-Treated Units as Control Group



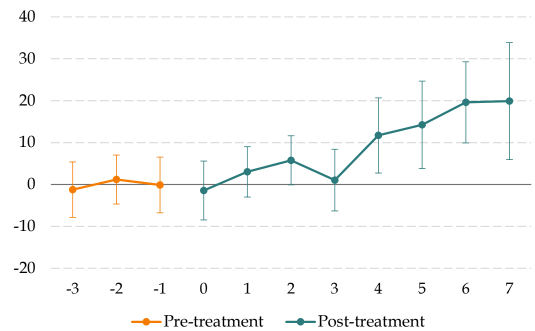
(a) USD 2.5 Poverty Line



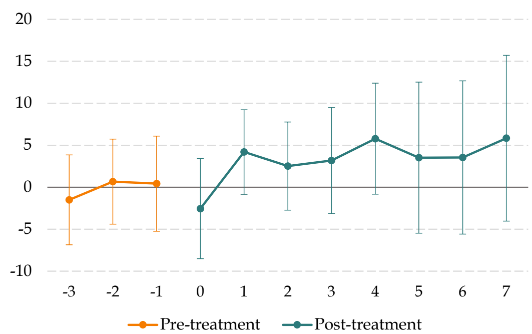
(b) USD 3.65 Poverty Line



(c) USD 6.85 Poverty Line



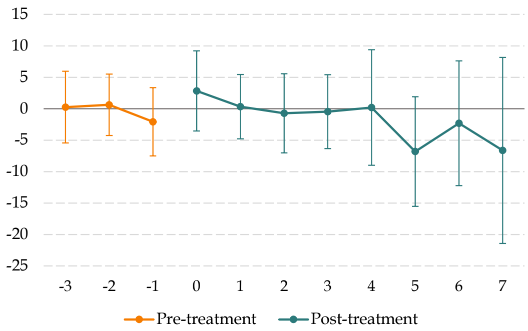
(d) Vulnerable



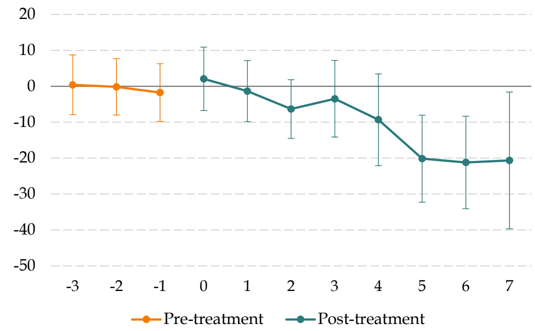
(e) Middle Class

Note: Not-yet-treated units are used as control group. 95% confidence intervals

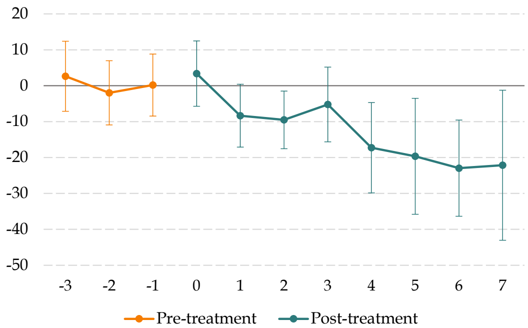
E Dynamic ATT Effects Under Unconditional Parallel Trends Assumption



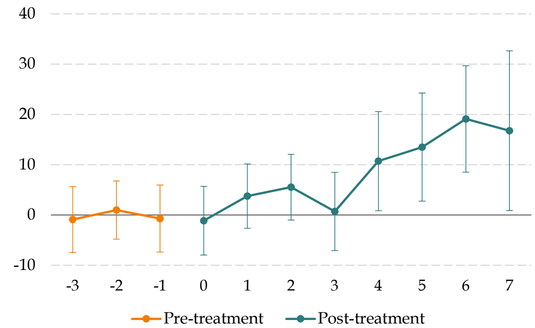
(a) USD 2.5 Poverty Line



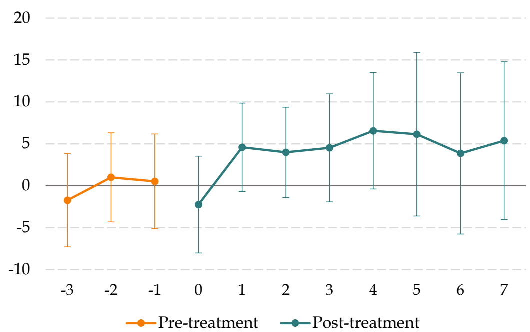
(b) USD 3.65 Poverty Line



(c) USD 6.85 Poverty Line



(d) Vulnerable



(e) Middle Class

Note: Never-treated units are used as control group. 95% confidence intervals