

Examining the socioeconomic outcomes of transport interventions in the Global South

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ABSTRACT

This paper addresses a recurrent distributive issue of transport interventions and aims to develop a framework of an impact evaluation of transport projects particularly tailored to the Brazilian context. The methodology draws upon the literature to employ a quasi-experimental approach performed by means of a difference in difference matching (DIDM) technique.

This technique is then applied to a case study in Northeast Brazil, in which the social impacts of a large transport project are analysed. Whilst many transport infrastructure projects have been advertised as key investments to promote regional economic growth, the results show that positive socioeconomic effects arising from these investments may not be captured by the least advantage groups of society. Findings subscribe to the view that transport infrastructure investments broadly contribute to the reduction of multidimensional poverty. This conclusion is particularly illustrated in this case study by the greater positive impacts in eleven socioeconomic indicators of the municipalities on the region of this transport project.

1. Introduction and background

This paper addresses this recurrent issue of transport planning and aims to develop a framework of an ex-post social impact assessment of transport projects particularly tailored to the Brazilian context. The methodology draws upon the literature to employ a quasi-experimental approach performed by means of a difference in difference matching (DIDM) technique since it has been considered an effective and robust method for this type of analysis by various authors in similar contexts (Chein and Pinto, 2017; Iimi et al., 2015; Rand, 2011; Rauniyar et al., 2011; Hansen et al., 2011).

This framework is then applied to a case study in Northeast Brazil, in which the social impacts of a large transport project are analysed. The selected project for this case study is the widening of the BR-232 motorway. There are at least three main reasons to believe that this particular transport infrastructure intervention is an appropriate and paradigmatic example to be investigated by this framework.

Firstly, the project was carried out during the latest intercensal period, between the years 2000 and 2010, which enables the Census' Demographic Database to be used for longitudinal comparisons. Whilst traditional panel data studies rely on expensive household surveys that require a lot of manpower to be performed and are often limited to a few

social indicators and few communities, this study proposes the use of census data that are publicly available and provide a comprehensive range of socioeconomic indicators of all municipalities before and after the infrastructure investment.

Secondly, this motorway (BR-232) has been only partially widened, leaving another considerable stretch with very similar socioeconomic, environmental and spatial characteristics rather suitable to be used as a control group. Fig. 1 presents pictures of this motorway showing the two different stretches, the original and the widened one. Google maps and google street view was used in this study as the research was conducted remotely.

Thirdly, this motorway is located in the Northeast region of Brazil, which beyond being an understudied region, is the region where extreme poverty is most widely spread in Brazil (Coirolo and Barbosa, 2002). Fig. 2 presents the location of this motorway in Pernambuco state, highlighting the stretch that has received the widening project (in red) and the stretch that still remains with the original number of lanes (in green).

Under these conditions, this paper aims to propose a well-grounded framework that uses publicly available data to evaluate how people living in different levels of poverty are affected by transport interventions in the Brazilian context. The research presented in this

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paper, the methods selected and the types of data used could be replicated in many other countries. The main issue addressed in this research is the lack of appraisal in the Global South and how this is linked to poor data and applying methods that are used in developing countries.

The remaining sections of this paper are divided into the brief description of the case study context; the methodology that is proposed and the required data; the presentation of the graphs and tables which resulted from this study; the discussion and policy implications that derive from this analysis; and, at last, a conclusions section.

2. Literature review

This literature review examines the previous works published that examine the links between the provision of new infrastructure, in the Global South, and the knock on socioeconomic impacts. Studies fitting these criteria are limited and our paper demonstrates the need for further work in this field. The first studies that examine the links between poverty and transport were published in the late 1960's and since then have become ever more frequent in the academic literature (Ornati et al., 1969; Hanson and Hanson, 1980; De Luca, 2007). A substantial amount of evidence has been published on ex-post evaluations of the contributions of transport infrastructure development to poverty reduction in many different countries (Stifel et al., 2016; Dillon et al., 2011; Dercon et al., 2009; Fan and Chan-Kang, 2008; Warr, 2005). It should be noted that in the Global South the evaluation of transport policies can be much more difficult due to the lack of data (Benevenuto and Caulfield, 2019).

Dercon et al., (2009), for instance, used generalised methods of moments to evaluate the socioeconomic effects of road improvements in rural Ethiopia. Their study has shown that the provision of access to all-weather roads has reduced poverty rates and increased consumption growth by 6.9 and 16.3 percentage points, respectively. Likewise, results reported by Fan and Chan-Kang (2008) show that 226 people from Northern regions of China were lifted above the poverty line for every additional kilometre of low-quality road in rural areas. Furthermore, Warr (2005) asserts that approximately 13% of the decline in rural poverty incidence which occurred between 1997–98 and 2002–03 in Laos can be attributed to improved road access alone.

Nonetheless, it is still unclear what effects transport infrastructure investments have in alleviating the most extreme levels of poverty. In fact, some authors advocate that people living in extreme poverty do not equally benefit from road constructions or roads improvements projects, mostly because walking is the only travel mode available/affordable for them (Salon and Gulyani, 2010; Setboonsarng, 2006; Cook et al., 2005).

in the long term, other positive effects initially observed on school enrolment, transport costs and per capita expenditure have attenuated over time.

Whilst policy recommendations derived from this literature suggest more public spending in transport infrastructure to foster economic development in remote and disadvantaged areas, a central question that requires attention is to what extent this development results real improvements in the well-being of the neediest population living nearby these projects. From a political philosophy perspective, Pereira et al. (2017) reinforced this question by applying the difference principle of the Rawls's Egalitarianism theory¹ (Rawls, 1999) to transport justice. They conclude that, through the lens of this principle of justice, transport infrastructure and other transport related investments can only be considered fair if they improve the accessibility levels of the least advantaged groups.

3. Context of the study

The state of Pernambuco, alongside with Bahia, was the place of the first Portuguese settlements in the Americas. Similar to other North-Eastern states in Brazil, the vestiges of its colonial past are still clearly visible nowadays. For instance, high levels of income inequality and political control by the same families whose origins date back to the sugar plantations of the 16th and 17th centuries are issues still present in the region (Griesse, 2007).

This state was included in the intercontinental study on poverty published by World Bank study, *Voices of the Poor* (Narayan et al., 2000). According to the population of Pernambuco interviewed by the authors of this study, unemployment was the main reason causing poverty in the state. Nearly two decades later, data from the Brazilian Institute of Geography and Statistics (IBGE, 2018) shows that the unemployment rate increase of most concern over the past years in Brazil happened in Pernambuco, increasing from 8.1% in 2014 to 16.9% in 2017. In terms of transport infrastructure, all main cities in Pernambuco are connected to the capital, Recife, through 41,657 km of roads, of which only 5548 km are paved (GEIPOT, 2000²). In a recent survey published by the Brazilian National Confederation of Transport (CNT, 2018), 94.9% of the state road network was considered in either regular, bad or extremely bad condition. Moreover, Railway transport is still very limited in areas close to the Recife metropolitan region, and waterway transport is restricted to the São Francisco basin (southwest border with Bahia state).

Four transport infrastructure projects have been announced as the future priority for this state by the National Logistic Plan (EPL, 2018).



Fig. 1. Road BR-232 - The original motorway on the left with just two lanes, and the widened stretch with four lanes on the right (Source: Googlemaps Streetview).

Similarly, Hansen et al. (2011) also argue that transport infrastructure interventions only impact people's well-being after a long chain of intermediate outcomes that interact with other investments, private as well as public, and geographical conditions.

Khandker and Koolwal (2011), for example, report that the benefits of rural road investments to households in rural Bangladesh have varied substantially over time. In a dynamic panel data study, these authors have concluded that while non-agricultural wage employment has risen

¹ Rawls (1999) defines the difference principle as a key concept of his theory of Justice, which governs the distribution of primary goods (e.g. wealth, positions of responsibility and power, government services). This principle maintains that inequalities in the distribution of primary goods are only permissible if it maximises the minimum level of them among the least advantaged population (similar to the maximin criterion, commonly referred to in the Economics literature).

² No more up to date figure has been found in official sources by the authors.

These projects refer to improvements in the roads BR-232 (between Salgueiro and Parnamirim), BR-316 (between the municipality of Parnamirim and Piauí state), BR-116 (between the municipality of Salgueiro and Bahia state), BR-101 (between the municipality of Palmares and Alagoas state).

It is important to emphasise that this plan, as well as the previous investments plans for transport infrastructure in Brazil have been solely driven by traditional demand and environmental analysis, disregarding, therefore, the social dimension and distributive effects at the planning stage. In the following sections of this paper, a case study will be provided, analysing whether the investment in the BR-232 has promoted, even if unintentionally, any improvement in any of the main poverty dimensions in the municipalities more closely affected by this intervention.

4. Data and methods

4.1. Data collation

Traditionally, ex-post studies assessing the social impacts of transport infrastructure require a substantial amount of data to be collected, usually by questionnaires in two or more periods of time, before and after the intervention – ruling out the possibility of doing this kind of studies on projects that occurred in the past. Moreover, ex-post evaluation methods normally require data collection in several different locations, for example communities, villages, or households that received the intervention (i.e. treatment) as well as the control ones. [Mu and Van de Walle \(2007\)](#), for instance, reports that 3000 households from 200 different communes were surveyed in four different years to collect the needed database for their study.

Besides being very costly and time-consuming, these methods can also give rise to politically difficult situations, as reported by [Iimi et al. \(2015\)](#). Before even starting the surveys, the authors report that the State Government of Tocantins (Brazil) decided not to interview people in the control group (which would not receive the intervention), because this could trigger frustration and dissatisfaction with the government, once they would know in advance that other communities would receive more transport investments than theirs. In this case, [Iimi et al. \(2015\)](#) had to use as a control group the population who was located around one transport intervention that due to a long delay in the project happened

projects that happened in the past; ii) it has one of the most comprehensive ranges of socioeconomic indicators at a municipal level; iii) census data are commonly available by all over the Global South; iv) it is reliable, official and free of cost information; and finally v) it is available in a time frame that usually is long enough for capturing all the direct and indirect benefits of a large transport intervention.

The results presented in our paper bring a new dimension to the analysis of transport projects in the Global South. The modelling approach, like many, does come with some caveats. Testing the validity of the results may be difficult. [Ravallion \(2007\)](#) asserts that this methodology is quite data demanding and, therefore, limitations in the spatial and timely disaggregation of this data might give rise to endogeneity (i.e. invalidation of causal claims due to non-observed variables) and heterogeneity (i.e. differences between groups not due to chance) issues when assessing the treatment effect (i.e. the outcomes) of transport investments on poverty reduction.

4.2. Social indicators

The main datasets utilised for this study were the Demographic Censuses of year 2000 and 2010, collected by the Brazilian Institute of Geography and Statistics (IBGE) and made available by the Atlas of Human Development in Brazil ([UNDP, 2010](#)). From the original datasets, 26 socioeconomic indicators at a municipality level have been collated to compose a multi-dimensional evaluation of poverty for the referred region. The selection of such a range of indicators builds on the concept of multi-dimensional poverty, widely explored in public economics and welfare literature ([Narayan et al., 2000](#); [Alkire and Santos, 2014](#)). The following dimensions are included in the present analysis:

- **Health:** This dimension includes two basic health indicators that are included in the Brazilian census, namely, the life expectancy (in years) and the child mortality (in child deaths/1000 live births);
- **Education:** This set of indicators is related to illiteracy and school enrolment (including creche, primary and secondary school, and higher education);
- **Income:** This dimension includes income indicators that measure intensity (average income) and extent (share of population) of three different poverty levels (i) extreme poverty (monthly per capita income up to R\$ 70.00³); (ii) poverty (monthly per capita income up to

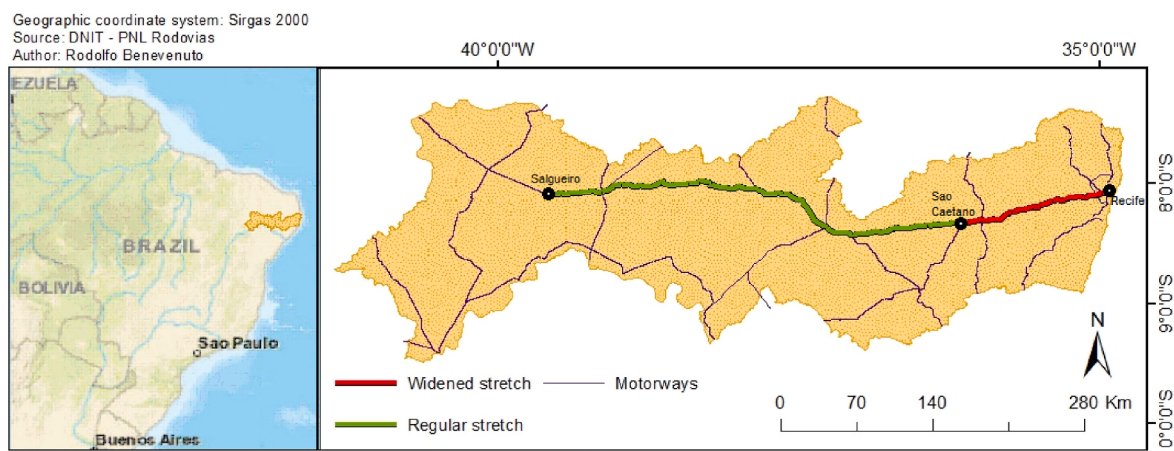


Fig. 2. Location of motorway BR-232 in Pernambuco state.

to not receive the treatment on time.

Under these circumstances, the study presented in this paper proposes an innovative methodology that requires publicly available census data alone for evaluating the social impacts of transport interventions. The advantages of using this kind of data are that i) it can be applied to

³ The minimum wage in 2010 was R\$ 510.00 a month – around US\$ 368.00 in 2010 purchasing power parity according to the conversion rate provided by OECD (2018).

R\$ 140.00) and; (iii) vulnerable to poverty (monthly per capita income up to R\$ 255.00), also disaggregated by overall and child poverty;

- **Wellbeing:** This block comprises the Human Development Index (HDI) and its disaggregation by income, education, and longevity;
- **Housing conditions:** This set includes indicators related to the housing characteristics such as the percentage of households with piped water, waste collection, electricity, or sewage facilities;
- **Inequality:** This dimension is evaluated by means of the GINI index,⁴ which measures the degree of income inequality experienced by a municipality;
- **Unemployment:** Finally, this is presented as the unemployment rates for each municipality, considering the share of the population of 18 years of age or more who were unemployed at the same month when the census data was collected.

Table 1 presents the indicators described above showing a comparison between the national figures and the values for the municipalities assessed in this paper.

4.3. Road infrastructure

The motorway BR-232, which is analysed in this case study, is considered as the transport backbone of the Pernambuco state since it crosses the majority of the state and it is the main east-west road connection of Pernambuco state. It starts at the capital, Recife, and goes 552 km inwards to the countryside, connecting main cities like Caruaru, Salgueiro, Sao Caetano, and Serra Talhada. The widening project was

Table 1

National and regional figures of the socioeconomic indicators included in the model.

Variable	Brazil	Sample of municipalities
Life expectancy [years]	73.9	71.0
Child mortality [child deaths/1000]	16.7	24.5
Creche enrolment rate [%]	55.0	56.2
Primary School enrolment rate [%]	92.1	92.1
High School enrolment rate [%]	43.4	33.0
Higher education enrolment rate [%]	14.0	6.1
Illiteracy (age of 15+) [%]	9.6	26.1
Average income per capita of the extremely poor [R\$]	31.7	34.4
Average income per capita of the poor [R\$]	75.2	72.2
Average income per capita of the vulnerable to poverty [R\$]	142.7	124.8
Extreme poverty rate [%]	6.6	18.4
Child extreme poverty rate [%]	11.5	26.8
Poverty rate [%]	15.2	36.9
Child poverty rate [%]	26.0	52.8
Vulnerability to poverty rate [%]	32.6	62.6
Child vulnerability to poverty rate [%]	49.4	78.7
HDI overall	0.7	0.6
HDI education dimension	0.6	0.5
HDI longevity dimension	0.8	0.8
HDI income dimension	0.7	0.6
Share of households with piped water [%]	92.7	72.5
Share of urban households with waste collection [%]	97.0	93.5
Share of households with access to electricity [%]	98.6	99.2
Share of households without sewage/water facilities [%]	6.1	15.2
GINI index	0.6	0.5
Unemployment rates [%]	7.3	8.9

⁴ The Gini Index is a measure of income inequality, varying from 0 (perfect equality) to 1 (maximum inequality) (UNDP, 2010).

performed between 2001 and 2005 only in the stretch between Recife and Sao Caetano (142 km).

According to the responsible authorities, only two other transport infrastructure projects of construction and widening of motorways were performed during this intercensal period in the Pernambuco state. Both projects (at the BR-101 and BR-104) were carried out on the east part of Pernambuco state, that is, at the same side of the widened stretch of BR-232. The information about the road network including dates, dimensions and its spatial distribution have been provided by the Brazilian National Transport Infrastructure Department (DNIT, 2018).

Two groups of municipalities were then identified: those within the influence area of the widened stretch of the motorway (treatment group) and those along the original stretch of the motorway (control group). Several authors have applied the concept of buffer zones (from 5 to 300 km) to estimate the influence area of a road over the surrounding communities (Chein et al., 2017; Asomani-Boateng et al., 2015; Ortega et al., 2014). The rationale for the size definition of these buffers, however, is not clear in any of these studies.

It is undeniable that large transport infrastructure interventions would cause a long sequence of direct and indirect socioeconomic effects that may reverberate and affect communities much farther than any predefined buffer. Nevertheless, following Tobler's first law of Geography (Tobler, 1970), it is reasonable to assume that a higher impact would, as a rule, affect communities that are closer to the intervention. In this sense, a few characteristics can be broadly considered to define the influence area around a given transport intervention.

In the present study, the average size of municipalities, presence of spatial barriers (e.g. rivers, mountains, shore, etc), type of infrastructure intervention, population distribution and density, as well as the aggregation level of the available data have been considered when estimating the influence area. Moreover, as municipalities from the same state have generally more similar characteristics of investments and public policies that could affect the local socioeconomic indicators (i.e. potential sources of endogeneity), an appropriate distance band limit is the border of the Pernambuco state. Therefore, a buffer zone of 20 km (on either side of the motorway) was applied to define the municipalities of the treatment and control groups of this study. Fig. 3 shows, the proposed catchment area results in a comprehensive sample of municipalities along the motorway BR-232 that is also confined within the territory of Pernambuco state. Fig. 3 also displays the poverty rate distribution in the year 2000 of the municipalities around motorway BR-232.

4.4. Difference in difference matching technique

This Section aims not only to describe the main method used in this paper, but also to give a clear rationale for the selection of the econometric tools and datasets that are applied. Fig. 4 presents a brief summary of the main potential methods considered in this paper, highlighting in each step the adopted models/datasets (in blue), and the rejected methodological alternatives (in grey) that did not meet the particularities of the case study context.

Assessing social outcomes of transport investments means understanding the context in which an intervention happens and the channels through which the impacts are expected to occur (Hansen et al., 2011). In the context of large infrastructure interventions, one of the most suitable and referenced approaches used for capturing these outcomes is the quasi-experimental design (Hansen et al., 2011; Ravallion, 2007). This approach, also known as a nonexperimental, or observational study (Ravallion, 2007), draws comparisons between groups to test for the effect of an intervention. Differently from the 'experimental method' in which samples are randomly assigned to treatment and control groups before the treatment, this empirical study estimates the effect of a treatment that have already occurred in the past. Thus, the target population is not necessarily selected through random assignment.

Among the methods that are suitable to this type of studies, the DID technique stands out as a particularly interesting model. The core

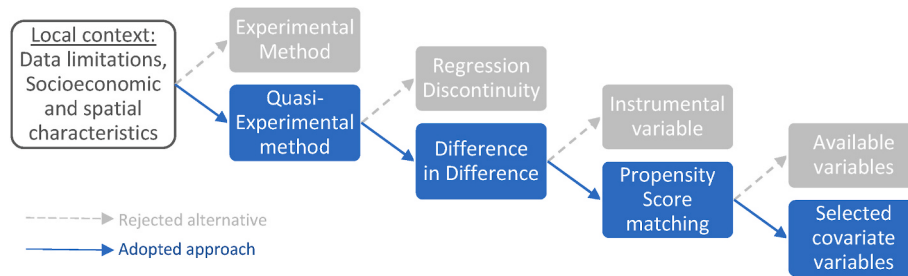


Fig. 3. Catchment area of the motorway BR-232 with poverty rates (%) before the completion of the project (year 2000).

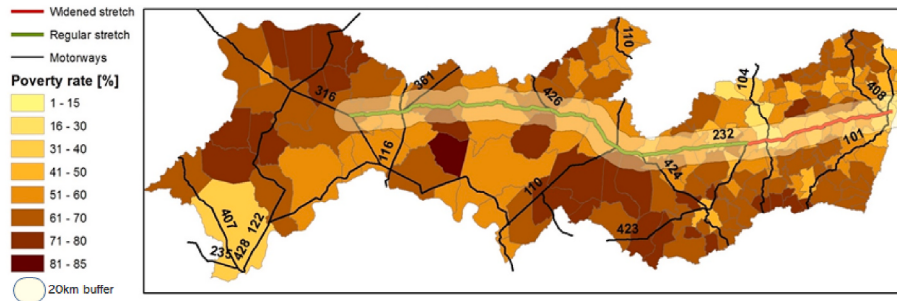


Fig. 4. Schematic summary of methodological alternatives.

principle of this method is to draw causal relationships between an intervention and its outcomes based on a longitudinal comparison between a treatment and a control group (Cook et al., 2002). One of its main advantages is that the pre- and post-test observations can be done using datasets such as the censuses, which are globally available and periodically updated. Allied to this, the DID model also compares the effects of an intervention between control and treatment groups, thus, reducing the bias of single difference comparisons.

A commonly used alternative to DID technique is the Regression Discontinuity design, which is applicable in experiments where cut-off criteria in the pre-treatment measures are used to identify participants in need of the intervention (William, 2006). Nevertheless, Lionjanga and Venter (2018) assert that this method is not suitable to evaluate the impact of transport interventions that do not present these cut-off criteria to determine the placement of intervention.

Hence, the DID method is adopted in the present study since it proposes an intuitive and well-grounded impact assessment that is suitable to most transport interventions. Based on this method, the social outcomes of the BR-232 motorway widening project are calculated as follows:

$$\Delta Y(m_i) = Y(m_i|t=1) - Y(m_i|t=0) \quad (1)$$

$$SocialOutcome = \Delta Y(m_i|G=1) - \Delta Y(m_i|G=0) \quad (2)$$

Where $\Delta Y(m_i)$ is the effect over time t (in which 1 represents the year 2010 and 0 the year 2000) observed in a vector of socioeconomic indicators Y (presented in Table 1) of the municipality m_i . The final social outcome (*SocialOutcome*) is then obtained by the difference between the effect $\Delta Y(m_i)$ of the treatment and control group. The dummy variable G differentiates the control and treatment group (being 1 the treatment and 0 for the control group).

To cope with observed confounding factors intrinsically associated with the context where the treatment takes place, many authors have suggested techniques such as Instrumental Variables (IV) or Propensity Score Matching (PSM) to be used alongside the DID technique (Chein and Pinto, 2017; Iimi et al., 2015; Cook et al., 2002).

Instrumental variables are often applied in quasi-experimental studies to control for endogeneity between the assignment into control/treatment group and the outcome. However, since the present case

study considers only municipalities along the same motorway (i.e. the group assignment is spatially restricted) in the samples, the use of Instrumental Variables is not applicable. In this sense, PSM emerges as the most appropriate method to reduce the bias when estimating the treatment effects caused by potential confounding factors of the samples.

4.5. Propensity Score Matching

Rosenbaum and Rubin (1983) define a propensity score (PS) as the conditional probability of assignment to a particular group (control or treatment) considering a number of observed covariates. Several confounding variables have been applied throughout the literature for the formulation of propensity scores in similar studies (Chein and Pinto, 2017; Iimi et al., 2015; Mu and Van de Walle, 2011). Ravallion (2007) states that these scores must be calculated based on a range of pre-exposure control variables, which can also include pre-treatment values of the outcome indicator.

Therefore, the PS offers a single numeric description of the initial context of the samples (municipalities/villages/neighbourhoods) in the analysis. In the context of transport studies, these confounding variables addressed in the literature mentioned above can be summarised in the following three levels in this study:

- **Demographics:** total population, GINI index, economic dependency per household, ethnicity rates, GDP per capita, poverty rates, etc;
- **Number of facilities/services available:** such as schools, enterprises, industries, police stations, banks (with credit availability) post offices, restaurants, markets, hospitals and motorways, as well as coverage of sewage, water piped, electricity, phone and internet resources;
- **Land use:** urbanisation rates, population density, size of arable areas, rural accessibility index (RAI), the presence of other infrastructure construction projects, etc.

Despite the lack of consensus on which variables should be included in PS calculation, according to Austin (2011) several studies in the literature have applied either i) all the baseline covariates, ii) just those

that affect the outcome, iii) just those that are associated with the treatment assignment, or iv) both (i.e. true confounders). Brookhart et al. (2013) assert that these variables can be also selected based on expert knowledge, as well as more empirical data-driven analysis relating the variables, the outcome and the treatment being analysed.

In the absence of a clear method defined in the literature, a number of trials with different combinations of the confounding variables mentioned above were carried out to determine the baseline covariates that would be considered in the composition of the PS for this case study. It was found that variables with extreme levels of variations - either too much (e.g. total population), or too little (e.g. GINI index) - have not resulted in a good balance between the number of confounding variables and number of matchings. Therefore, after this pre-assessment of the baseline variables the following five have been selected:

- 1 Gross Domestic Product (GDP)
- 2 Urban population rate (%)
- 3 Rural Accessibility Index (RAI)
- 4 Number of schools
- 5 Number of healthcare centres

The propensity scores (PS) are most commonly estimated by a logistic regression (Brookhart et al., 2013), which calculates the probability (*Prob*) of a given municipality (with a vector of its initial conditions indicators m_i) to receive the treatment according to its pre-treatment characteristics. Equation (3) represents how the propensity scores are given (Austin, 2011; Chein and Pinto, 2017).

$$PS(m_i) = Prob(G = 1 | m_i) \quad (0 < PS(m_i) < 1) \quad (3)$$

A sensitivity analysis based on the one-factor at a time (OAT) screening technique (Campolongo et al., 2007) is also proposed to clarify which factors have a higher influence on the outputs of the PS model. For doing so, the PS's are recalculated five times disregarding one of the baseline covariates at a time and then comparing the output variation in a graphical form.

Once the scores were calculated, six different strata were defined to maximise the number of municipalities included in the model as well as to preserve the recommended comparability level (less than a quintile each) among the groups. The municipalities were then ranked by PS and the matching process was done by proximity. The comparison between indicators from Treatment and Control groups was finally performed for every stratum according to Equation (4).

$$WSOi = \frac{1}{n_{total}} \sum_j n_j * SocialOutcome_j \quad (4)$$

Where, the weighted social outcome (*WSO*) of a given indicator (i) is calculated by the DID (*SocialOutcome*) given by Equation (2) for each stratum (j) of the propensity scores, weighted by the number of municipalities (n) included in each of these strata. This allows an estimative of the average impact of the transport intervention in each indicator (i) analysed in this case study. The use of weighted average in Equation (4) is important as the number of municipalities in each PS stratum are different. Therefore, it avoids the bias of over emphasizing the estimated impacts of smaller PS stratum in the total average (which would be the case if simple average was used).

In essence, the proposed methodology can be summarised in five main steps: i) Selection of relevant socioeconomic variables that will be evaluated before and after the transport intervention ii) Definition of the control and treatment groups based on the local socioeconomic context and characteristics of the transport intervention iii) Calculation of the PS for each municipality using a logit mode and the appropriate covariates iv) Definition of PS strata and matching o municipalities by proximity v) Calculation of the transport intervention effects over the socioeconomic variables of each PS stratum by comparing the difference between pre-post variation of the treatment group with the pre-post variation for

the control group.

5. Ex-post evaluation results

5.1. Propensity Score Matching

The first outputs of the proposed method were the PS calculated by the Logit Model for each municipality. Fig. 5 depicts the frequency distribution of the PS dividing the municipalities by control (blue) and treatment (red) groups. As can be observed, municipalities from the treatment group tend to have higher PS than municipalities from the control group. This result is a direct consequence of the higher urbanisation, as well as economic (GDP) and infrastructure (schools and healthcare centres) development⁵ levels of the municipalities along the widened stretch when compared to the control group.

This fact points to the heterogeneity issue that a simple comparison of outcomes (i.e. simple DID) between the two groups could lead to. Therefore, by undertaking a comparison of municipalities with similar propensity scores (i.e. by DIDM), the potential bias created by these confounding factors tend to be attenuated.

As previously described, the only two transport infrastructure projects delivered to this region in this intercensal period (other than the BR-232 widening project), were performed both along the widened stretch. Hence, any potential endogeneity which originated from these two projects would only exacerbate the differences between treatment and control group and would not diminish potential social impacts assessed by the model. Moreover, it is also assumed that investments in any sector (including new public transport services) other than transport infrastructure, are expected to be either very local (therefore dissolved in the averages or mitigated by PSM technique) or with similar effects throughout all considered municipalities since they are spatially concentrated in the same state. In other words, as large infrastructure investments are predominantly done at the state level in Brazil, and only municipalities from the same state (Pernambuco) have been selected in this study,⁶ further endogeneity factors tend to be evenly distributed throughout the municipalities, not affecting any of the groups specifically.

Once the PS's are calculated, the definition of the matching strata could then be carried out. Based on the distribution of PS's across municipalities, six different strata were proposed to maximise the number of matchings, while also keeping a comparable range of PS between the groups. In this sense, the municipalities with too high or too low PS (i.e. outliers) were not included in the DIDM analysis since no comparable municipalities were found within the considered samples.

As a result, from the original sample of 76 municipalities (35 from the control and 41 from treatment group), only 51 municipalities (23 from control and 28 from treatment group) were deemed fit for comparison within the six different PS strata. Simply put, 25 municipalities of the original sample had to be disregarded for not having a comparable pair in their opposing group.

5.2. Sensitivity analysis of the propensity scores

Fig. 6 illustrates the sensitivity analysis showing how the PS's values respond to variations of the input baseline covariates. The PS's of the municipalities are presented in ascending order to facilitate the interpretation of the graphs. In summary, the importance of an input variable in the composition of the PS's can be observed by the amount of variations occurred when the PS's are calculated without that variable.

The results show that the higher impact on the PS is caused by the percentage of the urban population in a municipality. This finding

⁵ Factors considered in the Logit model to estimate the PS.

⁶ Only municipalities within 20 km from either side of the road have been included in the samples.

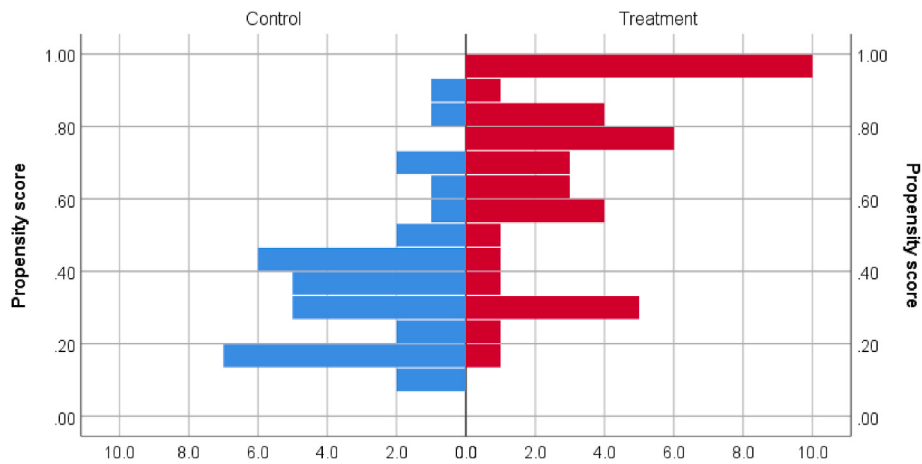


Fig. 5. Frequency distribution of Propensity Scores by group.

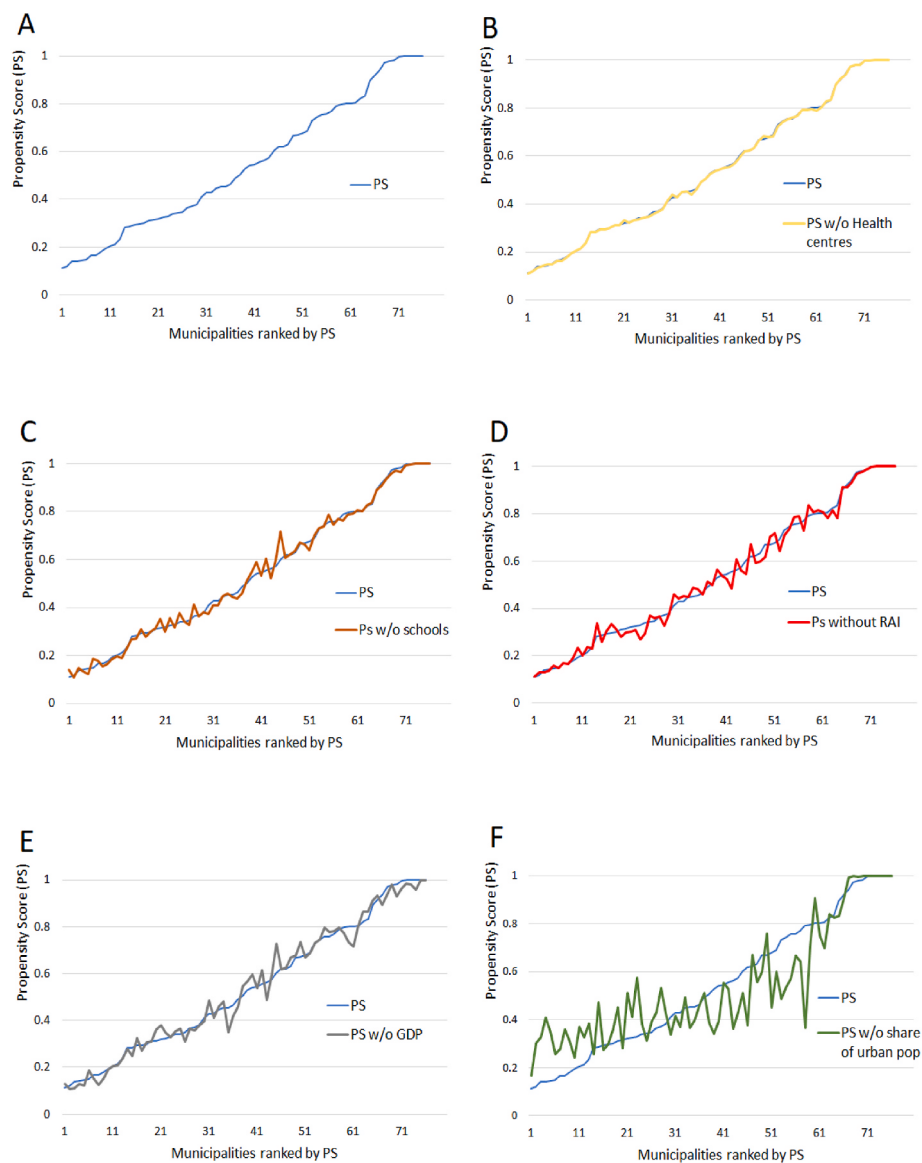


Fig. 6. Sensitivity analysis of the propensity scores across municipalities. A) Original PS B) PS calculated without the Healthcare centres variable C) PS calculated without the Schools variable D) PS calculated without the RAI variable E) PS calculated without the GDP variable F) PS calculated without the Share of Urban population variable.

highlights that these municipalities have quite similar levels of urbanisation when compared to the others from the same group, that is, municipalities from treatment group are overall more urbanised, and municipalities from control group are overall more rural. In statistical terms, this means that the *share of urban population* is the best explanatory variable of the proposed model to indicate whether a municipality belongs to the treatment group or not. At the second level of influence (with minor variations), there are other three variables, namely, GDP, RAI, and the number of schools. Lastly, the number of healthcare centres present the lowest level of influence, causing nearly no substantial variation when it is not included in the PS model.

Interestingly, while the standard deviation (in terms of percentage of the average) of the *share of urban population* was much lower than other variables, it has presented the highest impact on the sensitivity analysis of the PS. This fact highlights that wider variations of the input indicators do not necessarily imply in a higher impact on the generated PS. Table 2 presents the standard deviation values of such variables in terms of percentage of the average.

5.3. Social outcomes

A summary of the social outcomes of the BR-232 motorway widening project is presented in Table 3. This table shows a comparison between outputs obtained by two different methods, the DID technique (Equation (2)) and the DIDM technique (Equation (4)). For a better understanding of the social effects depicted in Table 3, the means of the 26 evaluated indicators are presented in Table 4 separating by time (before and after the project) and by group (treatment and control municipalities).

The purpose of this set of indicators presented in Tables 3 and 4 is to assess how people living in different poverty levels have benefited from the BR-232 transport investment. In general, the evaluated socioeconomic indicators have improved over time in both groups of municipalities (treatment and control). The only two exceptions among the twenty-six assessed outcomes were (i) the *average income per capita of the extremely poor* population, which has decreased (i.e. worsened) in the treatment group and increased (i.e. improved) in the control group, and (ii) the *share of households without sewage/water facilities* which has decreased (i.e. improved) in the treatment group and increased (i.e. worsened) in the control group.

Eleven out of the twenty-six assessed indicators (i.e. 42%) have presented in both methodologies (DIDM and DID) greater positive effects in the municipalities which have received the treatment. This shows that, in general, there was an overall social benefit of the project to widen the BR-232 motorway. Six out of these eleven, have presented substantial differences in the treatment group when compared to the control group.⁷ It is worth noting that the results reveal that *creche enrolment rate* was the indicator most affected by the widening project. The findings show that municipalities along the widened stretch of BR-232 had over 9.9% percentage points (pp) more creche enrolment after

Table 2
Standard deviation of the variables considered in the PS estimate.

Variable	Std. Dev.
Number of schools	146%
Number of healthcare centres	192%
GDP	443%
Share of urban population	35%
RAI	41%

⁷ For example, child mortality (9.03 pp more reduction), average income per capita of the population vulnerable to poverty (R\$ 4.71 more), child poverty rate (3.78 pp more reduction), poverty rate (3.32 pp more reduction), and the primary school enrolment rate (3.26 pp more).

Table 3
Comparison of estimated outcomes by DID and DIDM.

Variable	DIDM	DID
Life expectancy [years]	1.50	0.49
Child mortality [child deaths/1000]	−9.03	−1.78
Creche enrolment rate [%]	9.94	4.22
Primary School enrolment rate [%]	3.26	2.01
High School enrolment rate [%]	1.98	−0.78
Higher education enrolment rate [%]	−1.50	−0.27
Illiteracy (age of 15+) [%]	−0.97	0.51
Average income per capita of the extremely poor [R\$]	−2.06	−3.29
Average income per capita of the poor [R\$]	−0.22	−0.66
Average income per capita of the vulnerable to poverty [R\$]	4.71	3.66
Extreme poverty rate [%]	−0.27	2.43
Child extreme poverty rate [%]	−1.35	1.83
Poverty rate [%]	−3.32	−1.85
Child poverty rate [%]	−3.78	−3.55
Vulnerability to poverty rate [%]	−0.70	−2.29
Child vulnerability to poverty rate [%]	−0.05	−2.13
HDI overall	0.02	0.00
HDI education dimension	0.01	0.00
HDI longevity dimension	0.02	0.01
HDI income dimension	0.00	−0.01
Share of households with piped water [%]	4.30	−0.92
Share of urban households with waste collection [%]	−6.09	−7.79
Share of households with access to electricity [%]	−2.75	−7.30
Share of households without sewage/water facilities [%]	−9.35	−10.53
GINI index	−0.01	−0.01
Unemployment rates [%]	−1.91	−3.51

Table 4
Outcome variable means.

Variable	Before (2000)		After (2010)	
	Control	Treatment	Control	Treatment
Life expectancy [years]	65.3	66.0	70.3	71.5
Child mortality [child deaths/1000]	55.6	53.9	26.4	22.9
Creche enrolment rate [%]	36.3	38.4	52.8	59.1
Primary School enrolment rate [%]	89.0	87.5	91.8	92.3
High School enrolment rate [%]	15.1	15.9	33.0	33.0
Higher education enrolment rate [%]	2.0	2.0	6.2	5.9
Illiteracy (age of 15 or more) [%]	36.1	32.8	27.6	24.8
Average income p.c. of the extremely poor [R\$]	33.9	37.8	34.1	34.7
Average income p.c. of the poor [R\$]	59.8	71.2	66.5	77.2
Average income p.c. of the vulnerable to poverty [R\$]	89.9	107.3	113.4	134.5
Extreme poverty rate [%]	38.1	25.2	24.1	13.6
Child extreme poverty rate [%]	52.0	36.1	34.4	20.3
Poverty rate [%]	62.4	52.1	43.4	31.3
Child poverty rate [%]	76.8	66.6	60.2	46.4
Vulnerability to poverty rate [%]	82.0	75.4	67.3	58.5
Child vulnerability to poverty rate [%]	90.7	85.3	82.8	75.2
HDI overall	0.4	0.5	0.6	0.6
HDI education dimension	0.3	0.3	0.5	0.5
HDI longevity dimension	0.7	0.7	0.8	0.8
HDI income dimension	0.5	0.5	0.6	0.6
Share of households with piped water [%]	43.1	57.4	65.4	78.7
Share of urban households with waste collection [%]	72.3	82.2	92.4	94.5
Share of households with access to electricity [%]	88.5	96.7	98.7	99.6
Share of households without sewage/water facilities [%]	12.0	20.7	16.2	14.4
GINI index	0.6	0.6	0.5	0.5
Unemployment rates (age of 18 or more) [%]	9.5	16.0	7.2	10.3

the completion of the project than the other ones. The indicators related primary and high school enrolment also present the same trend of positive effects on education. These results are in line with findings from similar research published by [Lebo and Schelling \(2001\)](#), who have reported that primary school enrolment of girls in well-connected villages in Bhutan is three times higher than the unconnected ones.

Perhaps contrary to what was expected, the *average income per capita of the poor*, the *share of urban households with waste collection*, and the *share of households with access to electricity* have improved less in the treatment group than in the control group. By analysing [Table 4](#), it is possible to conclude that the access to electricity has improved more in the control group because the original share of households with access to electricity in the treatment group was already very high in the year 2000 (i.e. 96.7%). Leaving, thus, less room for improvement when compared to the original figure of the control group (i.e. 88.5%). The same argument can be made to explain lower improvements in the treatment municipalities in waste collection when compared to the control ones.

Finally, the findings also reveal that wellbeing and inequality indicators (i.e. HDI's and GINI index) have not presented significant differences between the groups. According to the data provided in [Table 4](#), it is possible to conclude that both dimensions have improved nearly at the same rate within the analysed time frame.

As described above, several socioeconomic indicators have shown higher improvements in the region where the road widening project was performed, compared to the control areas. Nevertheless, despite the positive impact on the broad socioeconomic outcomes of the study case region, a further analysis is still needed to compare how the least advantaged population have benefitted from the same transport investment.

5.4. Impacts on the least advantaged population

Even though substantial socioeconomic progress was found to be associated with the infrastructure intervention in the case study, these results should be interpreted with caution. The indicators related to the income dimension of poverty show that there has been a different impact on people living in extreme poverty and on people living in less severe levels of income poverty.

Whilst the average income per capita of people in *poverty* and people who are *vulnerable to poverty* have improved more in the treatment group over time, the same indicator for people in *extreme poverty* has actually decreased after the intervention. In other words, people surviving in extreme poverty in municipalities that received the transport project saw their average income decreasing over time. Additionally, the improvement in the treatment group was only modestly higher than the control one (0.23 percentage points) in terms of extreme poverty reduction. These differences point to a trend suggested by other studies ([Salon and Gulyani, 2010](#); [Setboonsarng, 2006](#); [Cook et al., 2005](#)) that extreme poverty is not necessarily alleviated by large transport infrastructure investments.

Similar to these findings, [Khandker and Koolwal \(2011\)](#) in a dynamic panel data study performed in rural Bangladesh also point out that households in extreme poverty may not be as able as the better off population to capture the productivity and cost reductions benefits of a road project. Likewise, [Setboonsarng \(2006\)](#) argue that despite evidence that transport infrastructure can indeed promote poverty reduction, this process is not automatic, and often the non-poor and less poor population benefit more from these investments than the neediest. Without complementary assistance to the poorest, [Setboonsarng \(2006\)](#) explains, these benefits are typically captured by the local elite.

Thus, the findings reported in this case study from Northeast Brazil support earlier evidence, showing that the benefits of a new transport infrastructure might vary significantly even among groups of lower income levels. This has important implications for planning new transport interventions, especially where extreme poverty is most spread, like in rural Northeast Brazil. The results of this ex-post assessment ultimately

highlight the need to assess the distributional impacts and screening the transport-related needs at a local level prior to massive transport infrastructure investments.

6. Policy implications

This study set out with the aim of structuring a framework capable of evaluating the social outcomes of transport interventions in Northeast Brazil using publicly available datasets only. Regarding the framework, the comparisons between the results obtained by DID and DIDM have highlighted potential misperceptions of a 'context-less' analysis. A set of five indicators have resulted in opposing conclusions when the outputs of these two methods were compared. This contrast emphasises the importance of using the PSM technique when estimating causal treatment effects in panel data studies like this. The findings strongly support the idea that if the context of the quasi-experiment study is not considered, the results may lead to biased conclusions being made on the relationships between a transport investment and its outcomes.

Whilst the results point to a wide range of positive socioeconomic effects that can emerge from the road widening project, they also call attention to the necessity of evaluating the distributive impacts of transport investments. As shown by indicators of average income per capita, it is not guaranteed that improvements on the transport infrastructure will result in welfare gains for the population in most need. This particular case study demonstrates that people in extreme poverty living in municipalities along the widened stretch had actually a decrease in their average income per capita after the completion of the project.

7. Conclusion

This paper has sought to evaluate the social outcomes of a transport infrastructure intervention in Northeast Brazil by developing and applying a well-grounded ex-post assessment framework. Whilst many transport infrastructure projects have been advertised as key investments to promote regional economic growth, this research sheds light on to the extent to which this development has also resulted in socioeconomic benefits to the least advantaged population.

Overall, the reported findings subscribe to the view that transport infrastructure investments broadly contribute to the reduction of multidimensional poverty. This conclusion is particularly illustrated in this case study by the greater positive impacts in eleven socioeconomic indicators of the municipalities on the region of this transport project.

Nonetheless, this research has also demonstrated that people living in the most severe levels of poverty do not equally benefit from large transport infrastructure investments. This is mostly supported by the decrease of the *average income per capita of the extremely poor* and by the modest decline of the *extreme poverty rate* in the municipalities along the widened stretch of BR2-232 when compared to the municipalities of the control group.

Thus, the proposed framework draws attention to a recurrent misperception that occurs when the distributional impacts of transport infrastructure interventions are disregarded at the planning stage. Despite overall socioeconomic progress, the findings have shown that complementary actions are still needed to ensure that these investments will result in a fair distribution of their benefits to society. It is argued that these additional interventions should be guided by ex-ante social impact analysis performed when appraising and prioritising transport interventions.

In terms of the methodology, it is possible to conclude that the framework proposed in this paper is particularly suitable for case study region, considering its data limitations. Perhaps the main advantage of this framework is that it does not require expensive surveys and highly disaggregated data to be performed since it is based on publicly available data only. Thus, it unlocks a myriad of possibilities of case studies to assess other transport interventions which occurred in the past during

intercensal periods, and to explore their social effects over time.

Future research, however, is still needed to address limitations related to the endogeneity and aggregation of spatial data highlighted throughout this paper. For regions where data is more spatially disaggregated, the same framework can be refined into areas smaller than a municipality to further explore spatial distributional effects. Moreover, the inclusion of other types of investments (other than transport infrastructure) as a means to reduce the bias potentially caused by endogeneity factors is highly recommended in further studies exploring this research line.

This research also makes a strong case for the debate about the large transport infrastructure investments that are currently in the pipeline of Pernambuco state (e.g. BR-316, BR-116, BR-101), as well as throughout the whole Country. The evidence reported by this study emphasises that these transport infrastructure interventions must not be disconnected from the local needs, and the distributional impacts must be considered at the planning stage if poverty eradication is a goal to be achieved within this generation.

Like all studies of this nature, our work is also subject to some limitations. The research presented in this paper has not investigated the direct impacts of transport infrastructure investments on health outcomes. Moreover, despite being reasonable to assume that neighbour municipalities with similar characteristics (translated by a similar propensity score) tend to be homogeneous in terms of socioeconomic conditions, other sources of endogeneity that could affect social development such as private investments, and targeted public initiatives in healthcare, education, and welfare have not been considered in this study. Also, the distributional impacts within the municipalities could not be considered beyond the rural/urban differences in this analysis since there was no further disaggregation of the publicly available datasets for these municipalities.

The estimated social outcomes were shown to be substantially dependent on which method is used to analyse the data. The analysis of nearly 20% of the indicators (5 out of 26) resulted in opposing conclusions depending on whether the DIDM method was used, instead of a simple DID. This fact emphasises the potential misperceptions of a 'context-less' analysis that can lead to equivocate transport policies.

The results also demonstrate that while this large transport infrastructure investment (a crossing-state road widening project) improved the overall levels of poverty-related indicators, the impact on the average per-capita income of the population in extreme poverty was actually negative. In other words, the findings show that the population surviving in extreme poverty had their average per-capita income reduced by 8.2% after the completion of the project, while the equivalent control group presented opposite trends for the same indicator. This empirical case study serves as a cautionary tale about how large transport infrastructure investments are not enough to guarantee extreme poverty reduction. Likewise, this fact underscores the necessity to evaluate the local needs and transport issues that mostly affect the least advantaged population when prioritising transport interventions.

The approach presented in this paper could be applied to other ex-post analysis of projects in the Global South. Our approach demonstrates how the benefits of transport infrastructure can go far beyond the traditional benefits in a cost-benefit analysis. We would recommend that policymakers and funding bodies examine these approaches and provide better guidance on the evaluation of transport infrastructure projects in the Global South. Further development, application, use, and refinement of the approach presented could improve the methods and provide a more holistic appraisal tool.

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