Highway Infrastructure and Local Outcomes: measuring causal effects of infrastructure investments using cost-related instrumental variables

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Abstract

An extensive number of studies has examined the role of infrastructure on economic growth and development. However, results vary critically due to the empirical design and methodology. In this paper, we propose a novel identification strategy using the main infrastructure project costs as instrumental variables for our highway investment variable. We use data on national highway investment to estimate the causal impact of road infrastructure on local (municipal) outcomes. Our results show that, conditional on controls, our cost related IV identification strategy is suitable at identifying highway impacts on municipal outcomes. Findings remain unchanged under several specifications. Using our preferred estimated elasticity of 0.01, we calculate a return rate to highway investment of 24.2%, demonstrating a high road infrastructure rentability in Brazil.

Keywords: Highway infrastructure; local development; instrumental variables; infrastructure costs.

Resumo

Uma vasta gama de estudos avaliou o papel da infraestrutura no crescimento e desenvolvimento econômico. No entanto, os resultados variam criticamente devido à abordagem empírica e à metodologia. Neste artigo, propõe-se uma nova estratégia de identificação utilizando os principais custos dos projetos de infraestruturas como variáveis instrumentais para o investimento em rodovias. Utiliza-se novos dados sobre investimento em rodovias federais para estimar o impacto causal da infraestrutura rodoviária em variáveis locais (municipais). Os resultados mostram que, condicional aos controles, a estratégia de identificação com variáveis instrumentais relacionadas com os custos dos projetos de infraestrutura é adequada para identificar o impacto da infraestrutura rodoviária nos resultados municipais. Estimativas permanecem inalterados sob várias especificações. Utilizando a elasticidade estimada de 0,01, calcula-se uma taxa de retorno do investimento em rodovias de 24,2%, demonstrando uma elevada rentabilidade da infraestrutura rodoviária no Brasil.

Palavras-chave: infraestrutura rodoviária; desenvolvimento local; variáveis instrumentais; custos da infraestrutura.

Área temática: Desenvolvimento Econômico.

Classificação JEL: O18; O47; C26.

1. INTRODUCTION

A massive literature has evaluated the infrastructure investments impact on local outcomes (Baum-Snow et al., 2020; Bird and Straub, 2020; Duranton et al., 2014; Faber, 2014). Since Aschauer (1989), most of the studies have shown a significant relationship between infrastructure and those economic related outcomes. However, these results vary critically according to the investigation context and the identification strategy used – associated with endogeneity issues and whether the study uses aggregate data at country, regional, or local level (Foster et al., 2023a; Foster et al., 2023b; Straub, 2011).

In this paper, we focus on the main issue on the empirical road infrastructure and regional development literature: endogeneity. First, road is not randomly placed as policymakers might target underdeveloped regions aiming balanced economic growth or developed regions to attend existing demands by transportation infrastructure. Second, measurement error bias often occurs, especially when using monetary infrastructure variables. Highway investments take time to mature and suffer from inefficiencies and delays specially in the developing world context (Calderón and Servén, 2014; Kenny, 2009; Straub, 2011).

Our main contributions are twofold. First, to measure the causal impact of national highway investments on local (municipal) economic development, we construct a new dataset of national investments flows at the municipal level from 2007 to 2018. To do this, we use Growth Acceleration Program (PAC) data on transport investment flows and georeferenced it at the municipal level. It allows us to work in an empirical design wherein the road investment is promoted by the highest (federal) government level, whilst the dependent variable is local, then reducing concerns on reverse causality bias.

Second, to correct measurement error and omitted variables bias, we propose a novel instrumental variable (IV) identification strategy based on the main infrastructure project costs in Brazil. Those IVs include geographical, environmental, and human physical (expropriation and interferences) costs. Conditional on an extensive set of controls, we argue that those IVs affect local outcomes just through the highway variable (Holl, 2012; Martin-Barroso, Nunez-Serrano, and Velazquez, 2015; Lu et al., 2022; Zhang, Hu, and Lin, 2020).

Our findings show that our identification strategy is suitable at identifying the causal highway investments impact on local outcomes, and OLS estimates are highly underestimated. These results remain unchanged under several robustness checks. Based on our preferred specification, we find a stable elasticity of 0.01, which is in line with a wide range of empirical studies on infrastructure. Using this elasticity, we calculate a return rate to highway investment of 24.2%, suggesting an (expected) high rentability of roads in Brazil.

Besides this introduction, the paper has five more sections. Section 2 briefly describes the related literature. Section 3 presents our cost related IV identification strategy and the rationality behind it. Section 4 describes the data. Section 5 presents the results. Section 6 concludes.

2. RELATED LITERATURE

2.1. Road infrastructure and regional or local economic development: empirical related literature

An extensive strand of literature has examined the relationship between road infrastructure and economic growth (Barzin et al, 2018; Baum-Snow et al., 2017; Baum-Snow et al., 2020; Bird and Straub, 2020; Ke and Yan, 2021; Rokickia and Stępniak, 2018; Zhang, Hu and Lin, 2020), productivity (Farhardi, 2015; Ghani, Goswami and Kerr, 2014; Holl, 2016; Huang and Xiong, 2018; Li et al., 2017; Martın-Barroso, Nunez-Serrano and Velazquez, 2015; Xu and Feng, 2022; Yang, 2018; Zhang e Ji, 2019), trade (Coşar and Demir, 2016; Duranton et al., 2014; Martincus et al., 2017), population (Adler et al., 2020; Baum-Snow, 2007; Duranton and Turner, 2012; Faber, 2014; Garcia-López et al., 2015; Gertler et al., 2019; Jaworski and Kitchens, 2019; Meijers et al., 2012; Percoco, 2015) and structural transformation (Albalate and Fageda, 2016; Asher and Novosad, 2020; Yang, 2018). Since Aschauer (1989), most of the studies have shown a significant relationship between infrastructure and those economic related outcomes. However, these results vary critically according to the investigation context and the identification strategy used – associated with endogeneity issues and whether the study uses aggregate data at country, regional, or local level.

In this paper, we focus on regional and local level studies. Infrastructure is spatial by nature (Straub, 2008, 2011), and a more geographically disaggregated view on the theme can clarifies some transmission channels. This is likely the reason why works using regional and local level data provide more heterogeneous results on the role of road investment on economic development (Foster et al., 2023a, 2023b; Roberts et al., 2019).

Then, we turn to the main empirical issue in the infrastructure-economic development empirical literature: endogeneity bias. First, measurement error bias often occurs, especially when using monetary infrastructure variables. Highway investments take time to mature and suffer from inefficiencies and delays specially in the developing world context (Calderón and Servén, 2014; Kenny, 2009; Straub, 2011). Second, the placement of roads is not random, as policymakers may target places that expect to growth more or promote growth in underdeveloped regions (Redding and Rossi-Hansberg, 2017; Redding and Turner, 2015). In this sense, we can also expect endogeneity issues coming from omitted variables and reverse causality.

Roberts et al. (2019) study a wide range of papers estimating the effects of transportation infrastructure on several outcome variables. Around 63,5% of them used identification strategies to address endogeneity concerns, of which 78% used reduced form estimations, and 52,6% utilized IV. Therefore, most of the papers relies on IVs, and studying this identification approach in detail is critical. In the next section we cover some of the main used IV approaches.

2.2. Main IV approaches in studies on the impacts of road infrastructure on regional or local development

The most part of the empirical literature on infrastructure and regional or local development have used IVs to identify causal impacts. These studies can be classified into a few main approaches based on the IV rationale and its measurement form. We draw upon Redding and Turner (2015), then we update this literature review and propose some advances. To this end, we also rely on Foster et al. (2023a, 2023b), which reviewed a massive number of empirical studies on infrastructure and development, including the road sector.

Redding and Turner (2015) identified three main IVs strategies. The first one, the planned route instrumental variable approach, is an instrumental variable strategy relying on planning maps and old documents as a source of quasi-random variation in the observed infrastructure (Baum-Snow, 2007; Bird and Straub, 2020; Duranton and Turner, 2012; Duranton et al., 2014; Frye, 2016; Hsu and Zhang, 2014; Michaels, 2008; Sheard, 2014; Herzog, 2021; Rokickia and Stępniak, 2018). The rationale behind this approach is that the planned routes were created to serve purposes quite different from those coming from modern infrastructure development we are trying to test (for example, impacts on GDP, population, or employment growth). Planned routes used in this approach are, for instance, the 1947 USA national interstate highway plan and the "Pershing plan" for US data, the Brasilia Road Plan for Brazilian data, the Japan's 1987 National Expressway Network Plan applied to Japan, and the project for a motorway network by E. Buszma dating from 1945 and the Resolution of the Automotive Council for the Council of Ministers plan from 1963 for the Polish case. A similar strategy was used by Sheard (2014) applied to the airport sector, using the USA 1944 National Airport Plan as IV.

The second approach, the historical route instrumental variable approach, relies on very old transportation routes as a source of quasi-random variation in observed infrastructure (Adler et al., 2020; Baum-Snow et al., 2017; Baum-Snow et al., 2020; Duranton and Turner, 2012; Duranton et al., 2014; Garcia-López et al., 2015; Holl, 2012; Holl, 2016; Hsu and Zhang, 2012; Lee, 2021; Martın-Barroso, Nunez-Serrano and Velazquez, 2015; Martincus et al., 2017; Percoco, 2015; Rokickia and Stępniak, 2018; Zhang, Hu and Lin, 2020). The validity of this kind of instrument requires that, conditional on controls, factors that do not directly affect economic activity in the localities of interest at the period of study (mostly the end of the twentieth century) determine the configuration of these historical networks. In other words, the validity of this identification strategy depends critically on the fact that the historical routes served different purposes (for instance, moving agricultural goods to local markets, achieving military, administrative, and commercial goals and so forth) than they have today (for example, to foster economic growth and employment). Several distinct IVs were proposed in this setting, including the 1898 railroad routes and the routes of major expeditions of exploration 1528–1850 for US data, a market access measure based on railroad network in 1870 for European regions data, the network of Roman roads for Italy data, the old Roman roads, the 1760 Bourbon roads, the 1760 Spanish postal route network and an accessibility to final markets in 1857 in the Spanish case, railway connections in 1952 for Polish data, locations of rail and tram stations in 1897, 1930, and 1960 for South Korea data, road and railroad networks in 1962 and postal routes in 1936 for China, and the Pre-Columbian Inca road network for the Peruvian case.

The third one, the inconsequential unit approach, relies on choosing a sample that is inconsequential in the sense that unobservable attributes do not affect the placement of infrastructure (Chandra and Thompson, 2000). Sometimes this strategy is combined with some planned or historical IV (Banerjee et al., 2012; Bird and Straub, 2020; Faber, 2015; Herzog, 2021; Percoco, 2015). In this approach, routes that sought to connect large centers cross (inconsequentially) small units (as a small city or municipality). Then, we expect that unobserved characteristics of these units which are between intended hubs are independent to the political and economic choice of the road.

Another strand of literature has utilized a Least Cost Path Spanning Tree IV (Faber, 2015; Frye, 2016; Ghani, Goswami, and Kerr, 2014; Huang and Xiong, 2018; Yang, 2018; Xu and Feng, 2022). This identification strategy tries to answer the question of which routes planners would have been likely to build if the sole policy objective had been to connect all targeted city nodes on a single continuous network subject to global construction cost minimization. To do this, a least cost path spanning tree network between large cites (generally classified as hubs) is generated based on global cost minimization. The identifying assumption is that this hypothetical highway network should affect city outcomes and the spatial allocation of industries only through the actual highway network, conditional on controls. The Least Cost Path approach has been used specially for Chinese data, with some cases for the USA and India.

A fifth approach uses cost-related environmental and geographical IVs (Holl, 2012; Martin-Barroso, Nunez-Serrano, and Velazquez, 2015; Lu et al., 2022; Medeiros et al., 2021a; Medeiros et al., 2021b; Zhang, Hu, and Lin, 2020). The rationale behind this identification strategy is that geographical costs directly affect road construction and maintenance, although they are exogenous factors in the way they have not direct relation with modern GDP, employment, wages, or productivity growth. This IVs are mainly measured as slope, terrain ruggedness, altitude, or elevation, and they have been used for Chinese, Spanish, and Brazilian data. The literature has also proposed cost-related IVs based on legal protected areas as a proxy for environmental costs, and demographic variables – for instance, populational density – to represent physical human costs as expropriation and interferences. We are not arguing that those kinds of costs are equal, but that they have similar attributes in the way they act as some of the main highway infrastructure costs.

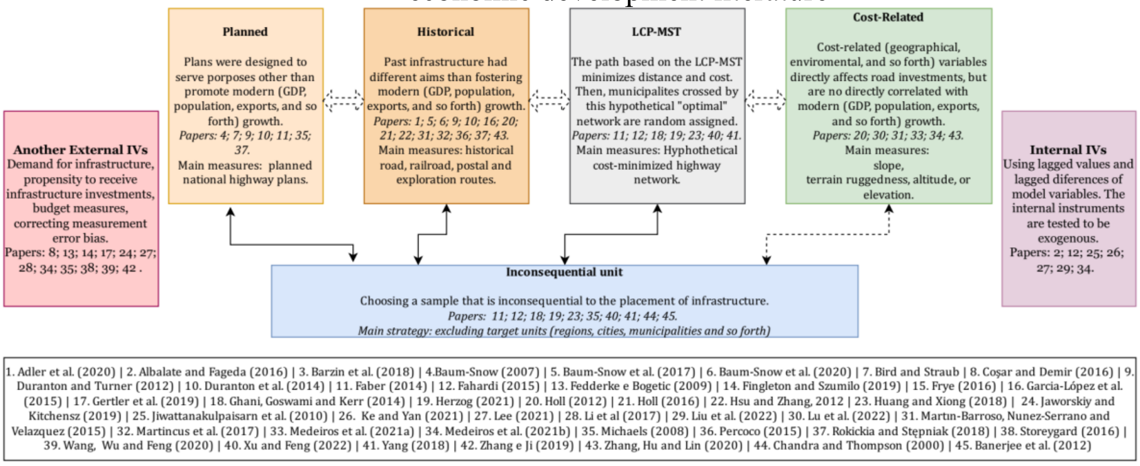
We can also identify another group of studies using different external IVs with different rationales. For instance, Coşar and Demir (2016) used the initial share of expressways as an instrument for provincial access to gateways. Fedderke and Bogetic (2009) constructed a demand for infrastructure IV based on the predicted demand for infrastructure stocks using time series econometric models. Baum-Snow (2007) combined the planned route IV with national construction rates over time as an IV. Storeygard (2016) used prices in instrumenting a road cost variable. Gertler et al. (2019) relied on national and provincial road budgets IVs. Zhang and Ji (2019) used lag populational variables to instrumentalize the road stock. As we can see, the IVs used in those studies are quite specific, unlike the other 5 approaches described before.

Using panel data models, some studies use internal instruments (lagged values and lagged differenced values of the model variables) in a GMM estimation setting (Albalate and Fageda, 2016; Bird and Straub, 2020; Farhardi, 2015; Fingleton and Szumilo, 2019; Jiwattanakulpaisarn et al., 2010; Ke and Yan, 2021; Liu et al., 2022; Barzin et al., 2018). In this case, the validity of the instruments can be tested using econometrics tests as the Hansen J. Some of those studies combine internal with external IVs (Gertler et al., 2019; Holl, 2012; Medeiros et al., 2021a).

Finally, another strand of literature has used an infrastructure reliance measure as an identification strategy (Li et al, 2017; Medeiros et al. (2021a); Percoco, 2015; Wang, Wu and Feng, 2020). The rationale behind this strategy is that industries that, for technological reasons, tend to rely less on transportation services (e.g., because they move heavier goods that tend to be more "road intensive" (Duranton et al., 2014), or because their employees do not need to travel long distances for business trips) act as a sort of control group for the "treated" ones, i.e. those that rely more on transportation services. This approach is particularly suitable when using sector or firm level data. Some investigations have used IVs to correct for potential measurement error in the infrastructure reliance measures (Li et al, 2017). Medeiros et al. (2021b) combine the infrastructure reliance approach with internal and external IVs to estimate the road impact on productivity in Brazilian economic sectors.

Figure 1 summarizes the main identification approaches – focusing on those using IVs – used in the infrastructure-development literature. The arrows indicate that exists some convergence between some of the identification approaches – for instance, some studies use both historical and cost-related IVs, or planned and historical IVs, or some combination of the inconsequential unit approach with some external IV, and so forth. On the other hand, in most cases, the studies classified as "other external IVs" propose specific IVs and are not much related with different frameworks. Similarly, the internal IVs, whilst combined with external IVs in a few cases, are mostly unrelated to the historical, planned, LCP or cost-related approaches.

Figure 1. Related empirical literature: main IV approaches used in infrastructure-regional economic development literature



Source: author's elaboration.

3. MEASURING CAUSAL IMPACTS OF ROAD INVESTMENTS ON LOCAL OUTCOMES: A NEW PROPOSAL BASED ON HIGHWAY INVESTMENTS COST-RELATED IVS

A way of dealing with measurement errors and omitted variables bias of road measures is choosing reliable cost-related IVs. Conditional on controls, cost-related IVs – for instance, geographical, environmental, and physical human costs as expropriation and interferences – might affect the outcome variable only through the highway variable (Holl, 2012; Lu et al., 2022; Martín-Barroso, Nunez-Serrano, and Velazquez, 2015; Zhang, Hu, and Lin, 2020). We may expect local terrain ruggedness making a road project unfeasible, which in turn is expected to affect a region or city economic development. Nonetheless, it is unlikely this observable characteristic will directly impact GDP, population, or another outcome variable growth. Similarly, environmental costs – as the extent or existence of legally protected areas – and physical human costs – as expropriation and interferences due to highly urban density – directly affect the feasibility and success of an infrastructure project but are unexpected to directly affect outcome variables.

This kind of IV may avoid (or alleviate) endogeneity bias in two ways. First, they may solve endogeneity issues related to omitted variables bias commonly found in infrastructure-economic development studies, as proposed by past studies (Holl, 2012; Lu et al., 2022; Martín-Barroso, Nunez-Serrano, and Velazquez, 2015; Zhang, Hu, and Lin, 2020). Second, they might act as a corrective instrument for measurement error bias of highway investment variables. This is particularly relevant when using monetary highway variables as investment flows in developing economies where a high inefficiency in allocating infrastructure investments is expected (Calderón and Servén, 2014; Straub, 2011).

Then, instrumentalizing the road variable by the main infrastructure costs may reduce both inefficiency bias - it is expected that more costly locations tend to have greater delays in buildings, making infrastructure investment impacts on outcome variables unclear - and road variable (specially the monetary ones) measurement error bias - for instance, more geographical, environmental and physical human costly locations may obviously demand a higher level of investment per length of road, requiring the construction of tunnels, bridges, expropriation and compensation payments, which might be reflected into heterogenous economic returns.

To better elucidate how cost-related IVs can directly affect road investments, we use some emblematic Brazilian cases. First, we briefly describe the iconic example of the BR-381/262 highway segment crossing the states of Minas Gerais (MG) and Espírito Santo (ES) to contextualize how cost-related inefficiencies occur in practice. The highway is noted by its poor quality and high traffic accident incidence and death rates, and buildings in many segments of the road has been demanded for decades. According to the CNT 2022 Highway Survey, one of the most critical segments of the highway, between the municipalities of João Monlevade and Martins Soares in the state of Minas Gerais, is in the 345-road quality position, out of 510 segments evaluated. According to data from the Federal Highway Police (PRF), the

BR-381 is the fourth highway in number of accidents and the fifth in accidents with deaths. Due to its critical safety and quality condition, the highway segment is known as the "Highway of Death".

The BR-381/262 (MG/ES) segment is also emblematic because its tough risks and project complexity. The road crosses areas with high population and urban infrastructure density, demanding huge additional monetary resources and time efforts to solve expropriation and interferences conflicts. Several delays occurred in the building schedule due to expropriation and evacuation conflicts, as many households did not accept the expropriation terms offered by the Brazilian government. Those issues indirectly affected the population welfare through its direct impact on the efficacy and efficiency of the investments in the highway. The conflictive status of the road required a long time to be solved and supplemental money to both attending the impacted population and maintaining built road segments which were not being effectively used by the society.

In 2022, the Brazilian Federal Government tried to grant the BR-381/262 segment (MG/ES). The result was the auction cancelation due to the lack of private partner interest. It was the fourth time that the “Highway of Death” auction was cancelled. The road sector private agents argued that the project was too risky – as it required massive investments and could suffer from several external interferences –, and it would require higher financial compensation to be taken.

A second interesting case is the BR-163 north segment between the states of Mato Grosso (MT) and Pará (PA). This segment was constructed in the 1970s, but it has never been completely paved until recently. The typical road segment picture was kilometers of stuck trucks for weeks during raining periods. As those trucks mostly carried perishable beans to the Brazilian north ports, they had several economic losses strictly associated with the road condition.

The BR-163 north segment is also symbolic because it crosses a large legal protected indigenous area. To mitigate potential negative environmental and social impacts of the road paving – as deforestation, illegal extractivism and so forth –, the Brazilian government released the “BR-163 Sustainable Plan” (Plano BR-163 Sustentável) in 2006. The plan was designed to improve the institutional quality of civil society organizations in the region in terms of its monitoring, evaluation, and information system, as well as expanding the mechanisms of social participation and control.

Due to its critical environmental sensibility, the BR-163 project received massive demands from environmental and indigenous organizations. To cover some of those requirements, the Environment and Renewable Natural Resources (IBAMA) listed 13 conditions to be met by the National Highway Infrastructure Department (DNIT) in paving the road. Among them, it included a study on the need to build passages for animals, a Monitoring Program for Water Courses, an implementation schedule for the Fire Fighting Program, and that the DNIT should inform IBAMA and the National Institute for Colonization and Agrarian Reform (INCRA) on the occurrence of *quilombola* communities found in influence of the highway segment. In practice, those needs implied additional economic and bureaucratic costs. In addition, the buildings in the BR-163 north segment were paralyzed several times due to native people interventions claiming for environmental protection and conservation. It incurred in several schedule delays and conflicts on land rights. Even in 2020, some BR-163 north segments were not fully paved.

Another segment of the BR-163 in the Serra da Caixa Furada in the state of Mato Grosso (MT) presented huge geological issues in a duplication building. In 2014, it occurred a landslide in the road, which implied 5 years of complete stoppage in the building. Due to its geology complexity, the building resumption and the reconstruction of the destructed highway demanded several additional financial efforts. The investments applied in the initial stage were rather inefficient as the population was not able to use the incomplete road duplication. In addition, more money was required to recover the collapsed highway segment and to maintain the already constructed (but not used) road segments.

The high infrastructure project risk heterogeneity in Brazil, which resulted in empty auctions as in the “Highway of Death” case, forced the Brazilian road sector authorities to rethink the assumptions guiding the rate of return methodology used to establish tariffs and economic-financial balances in the sector. Recent resolutions (6.002/2022, 6.003/2022 and 6.004/2022) on the calculation methodology of the Weighted Average Cost of Capital (WACC) were approved in December 2022 by the National Land Transportation Agency (ANTT).

The pivotal new resolutions aim was to include the main risk components in road infrastructure projects to calculate the federal highway sector WACC. To do so, the ANTT established several measurable indicators related to traffic demand, geographical, environmental, and physical human costs in road projects. For instance, the responsible actors must report the road length crossing legal protected areas, urban areas, and hilly areas. Also, the ANTT 6.002/2022 resolution included measures related to road projects expropriation and interferences costs, illegal urban occupation, and traffic demand risk.

Whilst the new resolutions focus on new road concession projects – including both brownfield and greenfield projects –, they provide us some reliable (and measurable) indicators that can be adapted to predict the feasibility and correct measurement errors of different types of road investments, as building, paving, duplication, enhancements and so forth. As the new ANTT methodology relies on real infrastructure projects, they are based on computable and highly replicable measures. Relying on the infrastructure-development literature (Holl, 2012; Lu et al., 2022; Martín-Barroso, Nunez-Serrano, and Velazquez, 2015; Medeiros et al., 2021; Zhang, Hu, and Lin, 2020) and measures based on real Brazilian infrastructure project costs, in the next sections we propose some cost-related IVs to overcome endogeneity issues in road variables.

4. DATA

4.1. National highway investments

To measure the impact of national highway investments on local (municipal) economic development, we construct a new dataset of national investments flows at the municipal level from 2007 to 2018. To this end, we use two main publicly available datasets.

The first one concerns data of investment flows in the highway sector of the Federal Government's Growth Acceleration Program (PAC). This dataset includes annual information on road investment flows for each one of the 27 Brazilian states, including a brief description of each intervention. As an illustrative example, it is reported whether there was a building intervention on Highway 1 between Local X (it can be the name of a municipality, the number of a km of a road or other local as a port, a connection with another road infrastructure as state or municipal and so forth) and Local Y. The data allows us to differentiate interventions in ROAD construction, duplication, or maintenance.

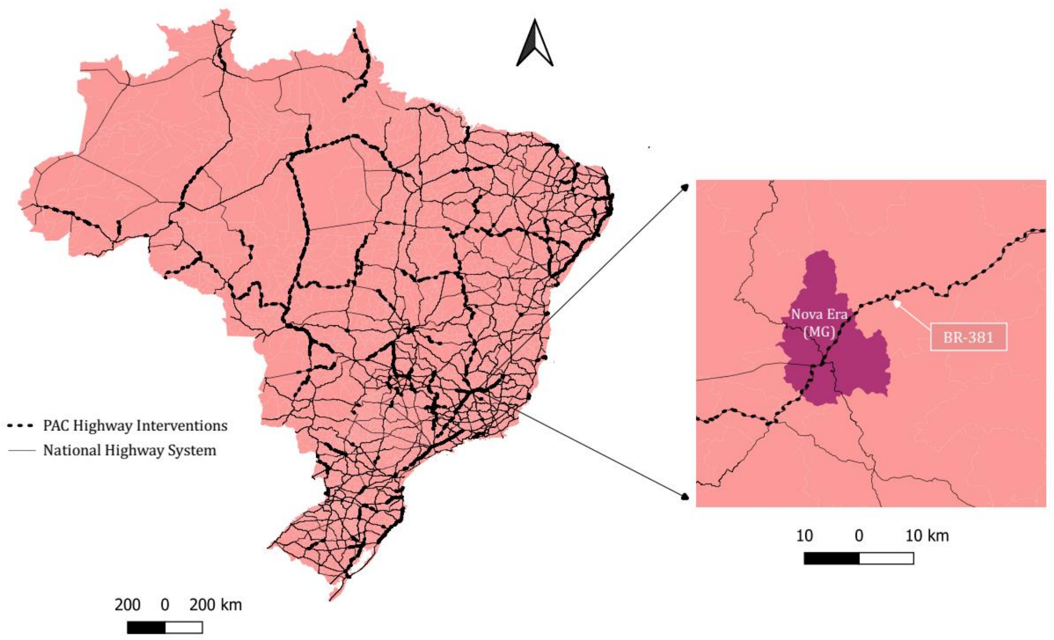
The second one refers to the National Highway System (SNV) georeferenced road data made available by the National Highway Infrastructure Department (DNIT). From this data, it is possible to identify the length of each road segment, its condition (paved, duplicated and so forth), and the places (municipalities) crossed by each one of the interventions road segments.

The PAC dataset is not georeferenced, which implies we have restricted information about whether and in which extent a municipality is crossed by an intervention. To create a national highway investment dataset at the municipal level, we combine the PAC's data description of each intervention and the georeferenced SNV data.

The first step was to identify the treated highway code and its starting and ending points from the intervention description of the PAC data. Next, the PAC treated highways were linked to the SNV geolocalized data using the highway code and their starting and ending points. It should be noted that the starting and ending points of the two datasets are not fully compatible, which made it necessary to manually match them one by one.

Second, we calculated the total PAC intervention road length by municipality and use it to measure the share of the road length in the municipality in relation to the total intervention road length. As we have investment data only by intervention, we use the measured share to compute the highway investment by municipality. It should be noted that the maintenance interventions description barely describes the state or highway code. In this sense, it was not possible to geolocate this type of investment at the municipal level, and they were excluded. Therefore, the investments refer to building and paving, and duplications and enhancements. The Figure 1 exhibits the PAC highway interventions.

Figure 2. Federal Highway Investments: Municipal Data Construction

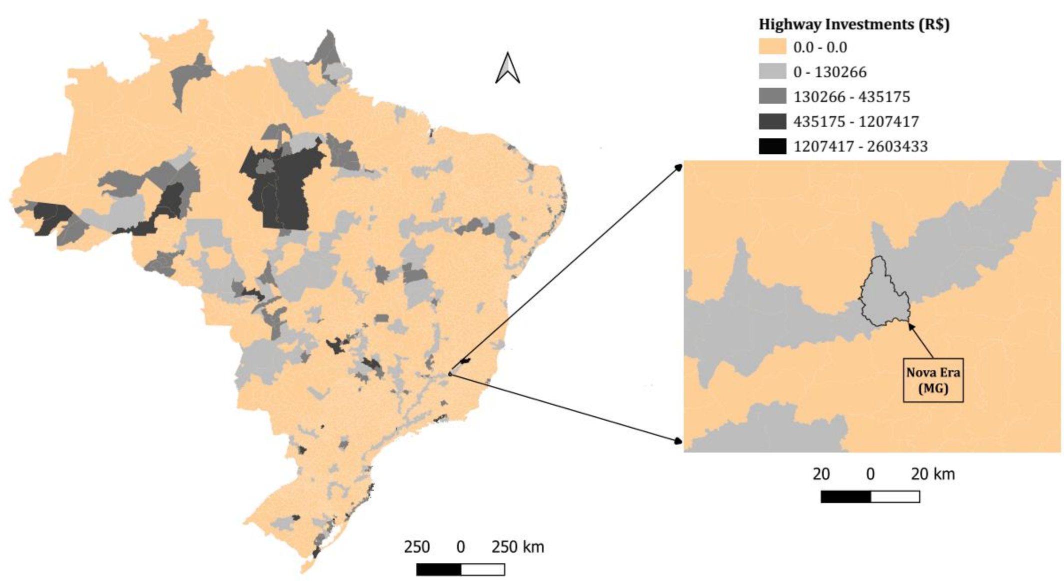


Source: Authors' elaboration. Note: white lines show the municipal territorial boundaries.

To illustrate how the proportion was measured, we take the example of the municipality of Nova Era, which was crossed by an PAC intervention in the highway BR-381. The total road length covered by one of the buildings in the BR-381 was 163 km, whilst the total investment on it in 2009 was R$ 10.8 million. Around 25 km (15%) of the intervention road segment crosses Nova Era. Multiplying the road-intervention proportion of 15% for Nova Era by the total intervention highway investment, the municipality directly received around R$ 1.6 million investments in 2009. Then, the same procedure is performed annually for all interventions and treated municipalities.

Figure 2 shows the PAC highway investments distributed by municipality between 2007 and 2018. The program directly reached out 703 municipalities, totalizing R$ 77.3 billion, excluding investments in road maintenance. This data is particularly relevant as granular data on infrastructure investment is limited (Brooks and Liscow, 2019). In most cases, data is aggregated nationally, and it is hard to standardize.

Figure 3. Federal Highway Investments by Municipality



Source: Authors' elaboration. Note: white lines show the municipal territorial boundaries.

4.2. Road investments cost-related IVs

To construct the cost-related IVs we use a set of variables representing environmental, geographical and expropriation costs at the municipal level. The next subsections describe in detail the used variables.

4.2.1. Environmental costs

At the environmental scope, we use georeferenced data of legal protected areas available in the National Registry of Conservation Units (CNUC), maintained by the Ministry of the Environment (MMA). Then, we merge this data with the municipalities boundaries shapefile to identify whether a legal protected area intersects a municipality. Our variable is a dummy which assumes value 1 if the municipality is intersected by a legal protected area and 0 otherwise.

Second, we utilize the environmental embargo terms data of the Brazilian Institute of Environment and Renewable Natural Resources (IBAMA) inspection system. Environmental embargoes represent penalties applied to prevent an exploratory activity from continuing. The embargos also serve to prevent ongoing damage and promote environmental recovery. For instance, penalties are applied to prevent activities with potential to damage environment, such as deforestation, pollution, and hunting. The application of environmental embargoes by IBAMA occurs mainly in cases where the degradation or damaging activity involves permanent legal protected areas. To generate our variable, we first aggregate the number of embargoes in the five previous years (2002-2006) from the PAC by municipality. Hence, we create a dummy variable which assumes value 1 if there was an environmental embargo in the municipality during this period and 0 otherwise.

We also try the share of forest area in relation to the total municipality area in 2006 as a third option. This variable came from MAPBIOMAS (Souza et al., 2020) land cover and land use data, which can be obtained at the municipal level.

It is important to point out that the institutions accountable for the data are utterly independent from the municipalities. The legal protected areas data are administered by the Brazilian (federal) environmental protection system and are controlled by the Chico Mendes Institute for Biodiversity Conservation (ICMBio), as part of the National System of Nature Conservation Units (SNUC). IBAMA is a federal agency related to the MMA. In this sense, concerns about the environmental IVs exogeneity condition are quite reduced.

The rationale behind the environmental IVs is that they impact the feasibility and the efficiency of a highway investment. Conditional on controls, we can expect environmental issues causing delays and rising infrastructure projects costs, which in turn may (indirectly) affect outcome variables.

4.2.2. Geographical costs

To construct geographic-related IVs we rely on a few studies measuring infrastructure effects on local outcomes using this kind of identification approach (Holl, 2012; Lu et al., 2022; Martin-Barroso, Nunez-Serrano, and Velazquez, 2015; Medeiros et al., 2022; Zhang, Hu, and Lin, 2020). All those works utilize some measure based on slope, elevation, ruggedness, altitude, or similar geographical variable.

Our preferred measure is the share of the municipality area with slope above 20%, which corresponds to hilly areas. To calculate this variable, we use slope raster data from the National Institute for Space Research (INPE), which allows us to count the number of slope pixels above the 20% cutoff. Then, we generate the share of hilly pixels in relation to the total pixels as our main geographic IV. We also try the municipal average altitude as a second geographical IV, also made available by INPE. Finally, we use a water resources-based variable which is the is the share of the area of mass water in relation to the total area of the municipality. To do this, we use water mass geolocalized data from the National Information System on Water Resources (SNIRH) of the National Water Agency (ANA).

Like the environmental cost IVs, we expect an indirect impact of geographic costs on outcome variables through the infrastructure measure. Geology complexity tends to raise the level of road investment as well as its efficiency. Then, it will be (or not) translated into economic benefits depending on delays and road project costs.

4.2.3. Expropriation and interferences costs

To quantify expropriation (human) costs we use urban infrastructure building and demographic variables, and land conflict variables. In the urban context, our preferred variable is the share of urban infrastructure building in relation to the total municipality area. For this, we used land use and land cover data made available by MAPBIOMAS (Souza et al., 2020), extracted at the municipal level. Our second measure is populational density, measured as the number of inhabitants divided by the area (km²) of the municipality in 2000. The source is the 2000 Demographic Census of the Brazilian Institute of Geography and Statistics (IBGE).

The rationality of these IVs is that physical human costs – as expropriation and interferences – will demand more resources and time to build road projects, conditional on controls. In this way, they also affect outcome variables trough infrastructure. In this case, however, we need to be further careful in including control variables as physical human costs are expected to be highly correlated with demographic variables.

4.2.4. Dependent and control variables

Our main dependent variable is the Gross Domestic Product (GDP), as it is the most commonly used measure in the infrastructure-development literature. As robustness checks, we also use GDP per capita as a productivity measure, employment, and wages. We are not able to use population data as Demographic Census have decennial periodicity in Brazil.

To avoid omitted variable bias, we include an extensive set of controls (see Table 1A in Appendix A for more details). Our control variables are based on the same group of studies described previously, and include some specificities related to the Brazilian case.

First, we include de initial level of the dependent variable as a control to capture the level of development. Municipalities with different levels of development can present different returns for infrastructure investments. Also, this variable controls for convergence effects (Cosci and Mirra, 2017). It is an important control as policymakers may act to promote balanced economic growth.

As road infrastructure is served by the federal and state level governments, we include state fixed effects to control for regional infrastructure policies. This variable also controls for other types of state fixed effects - as geographical, environmental, and political. This control is also relevant because the PAC realized several investments in road maintenance. However, road investment data is only available at the state level and cannot be disaggregated by municipality. In this sense, this fixed effect controls for omitted variable bias of other types of PAC road investments.

Municipality area is included to control for territorial size. Also, this controls is important as our main infrastructure variable is based on the PAC road length crossing a municipality area. Then, including this variable is important to not confuse the true highway investments impacts with the highway impacts in a municipality that has just a large area, then receiving more investments because it has a longer highway extension. In addition, this variable also accounts for the possibility that smaller/larger places may have other systematic differences such as quality of governance (Bird and Straub, 2020).

We include some controls related to the agricultural sector. The PAC period coincided with a period of basic products prices appreciation. If governments aimed at meeting the existing demands of their growing economic sectors, investments in infrastructure may have been partly due to the performance of agriculture sector in the period (Medeiros, Ribeiro and Amaral, 2021). Then, municipalities specialized in agriculture may have been more likely to receive federal road investments. Whilst agriculture share is the most common control, we also include rural credit as we believe this variable capture more adequately the public policies goal of attending agricultural specialized regions.

Similarly, infrastructure investments are seen as an important determinant of exports performance (Coşar and Demir, 2016; Duranton et al., 2014). Exporting municipalities may have received a higher priority in the allocation of infrastructure investments in the period of good performance in the international market. Then, we include the share of exports of each state in the national exports as control.

We also include a set of controls related to complementary infrastructures. Municipalities well connected with federal and state road network as well as port and rail infrastructures might be able to benefit more from national road investments. For example, municipalities served with high quality state road network can observe a greater impact of federal highways investments, as these roads may complement other well-established infrastructures. Then, we include the distance (km) to the nearest port, railroad, federal road and state road as controls.

Next, we include two controls for the propensity to a municipality to receive federal road investments. The first one is the traffic intensity in federal roads, which is a dummy variable assuming the value 1 if the municipality was crossed by a highway with heavy traffic in 2006, and 0 otherwise. This variable controls for the propensity of municipalities to receive investments because of a repressed demand for road infrastructure. The second one is the number of railway stations in 1920, the main transportation sector in that period. This variable controls for the propensity of municipalities to receive highway investments because they are historically well located in the country's transportation network. Those controls are particularly important to the validity of our physical human (interferences and expropriation) IVs, as they are correlated with demographic variables. In addition, controlling for those variables also alleviates the problem of non-random allocation of federal investments.

Finally, we include some controls related to the municipal social and institutional background. Those controls are extremely relevant, specially to avoid validity issues on our geographical IVs. Geography is the key determinant of climate and of natural resource endowments, and it can also play a fundamental role in the disease burden, transport costs, and extent of diffusion of technology from more advanced areas that societies experience. It therefore exerts a strong influence on agricultural productivity and the quality of human resources (Rodrik, Subramanian and Trebbi, 2004). In this sense, we first include Gini Index as a measure of income inequality. Inequality is correlated with the provision of public services (Bhattacharya, Saha, and Banerjee, 2016), including urban and local road infrastructure, which might impact the way of how road investments affect municipal outcomes. We also include the population share with higher education as a proxy for local social development. Third, we include municipal homicide rate as a proxy of institutional quality.

5. EMPIRICAL RESULTS

5.1. Descriptive analysis and preliminary tests

First, we observe some correlations and preliminary tests on the IVs. In unreported figures we show the correlation matrix including the highway investments variable and the proposed cost-related IVs. The infrastructure variable is positively associated with environmental and expropriation IVs and negatively with geographical IVs. Obviously, in most cases, IVs correlate more strongly with other IVs of the same type. For instance, urban infrastructure and population density are highly correlated as well as are legal protected areas and environmental embargos or sloped areas and altitude. The lower correlation between IVs of different types might suggest that those variables capture different spectrums of infrastructure project costs. It is important to note some IVs presented a very poor correlation with the highway variable, which places some caution on the following analyses.

Table 1 shows naïve OLS estimations on the relationship between highway investments and cost-related IVs. We include the full set of controls. Results corroborates the relationships observed in the correlation matrix. As we can see, the estimated coefficients for forest area and water mass are not significant, likely indicating a weak IV issue. In Column 12 we include all IVs together, which makes the density population coefficient to become non-significant. This is probably due to the high correlation between the expropriation measures. To overcome this issue, in Column 13 we include the three indexes for environmental, expropriation and geographical costs, and in Colum 14 we include an index for all the three cost types. Results suggest that all cost-related indexes are significantly correlated with the highway investment variable.

Table 1. Highway Investments and Cost-Related IVs: Naive OLS Regressions

	1	2	3	4	5	6	7	8	9	10	12	12	13	14
Legal Protected Areas	0.174***											0.165***		
	(0.05)											(0.05)		
Environmental Embargos		0.164***										0.124**		
		(0.05)										(0.05)		
Forest Area			-0.029									0.071		
			(0.06)									(0.07)		
Environmental PCA				0.188***									0.213***	
				(0.05)									(0.05)	
Urban Infrastructure					0.261***							0.275*		
					(0.09)							(0.15)		
Populational Density						0.161*						-0.055		
						(0.09)						(0.15)		
Expropriation PCA							0.223**						0.208**	
							(0.09)						(0.10)	
Sloped Area								-0.240***				-0.248***		
								(0.06)				(0.06)		
Altitude									-0.413***			-0.394***		
									(0.06)			(0.06)		
Water Mass										0.098		0.017		
										(0.06)		(0.06)		
Geographical PCA											-0.299***		-0.325***	
											(0.08)		(0.08)	
Cost-Related														0.408***
														(0.12)
Constant	-4.739***	-4.818***	-5.163***	-4.528***	-3.951***	-4.571***	-4.205***	-4.880***	-5.780***	-4.732***	-5.016***	-3.494**	-3.608***	-3.881***
	(1.29)	(1.28)	(1.29)	(1.29)	(1.30)	(1.28)	(1.29)	(1.28)	(1.28)	(1.34)	(1.33)	(1.36)	(1.35)	(1.34)
Observations	5472	5472	5470	5470	5460	5472	5460	5472	5472	5314	5314	5305	5305	5305
R^2 Adjusted	0.155	0.154	0.153	0.155	0.155	0.154	0.154	0.155	0.161	0.155	0.159	0.169	0.162	0.156

All regressions include the following set of control variables: : initial (2007) value of GDP; state fixed effects; municipality area; exports by municipality (% total); rural credit per capita; distance to the nearest federal road; distance to the nearest state road; distance to the nearest port; distance to the nearest railroad; homicide rate; Gini Index; higher education (% population); employment; agriculture share (% GDP); traffic intensity on federal highways; number of railway stations in 1920. Robust standard errors reported in parentheses. * 0.1 ** 0.05 *** 0.01.

5.2. Long-difference model

Our main objective is to estimate the long-term effect of improvements in highway network on our outcome variables at the local (municipal) level. Our main second stage equation is given by:

$$\Delta Y_{is} = \beta_0 + \beta_1 \Delta HighwayInvestments_{is} + X'_{is}\beta_3{}' + \theta_s + \varepsilon_{is} \quad (1)$$

Where Y_{is} is our dependent variables for municipality i in state s, $HighwayInvestments_{is}$ is the log form of the federal highway investments, X'_{is} is a vector of control variables, θ_s is a state fixed effect, β_0 is a constant term, β_1 is the elasticity of highway investment to our dependent variable, $\beta_3{}'$ is a vector of parameters related to the control variables and ε_{is} is the idiosyncratic error term. The term Δ the change in our dependent variable between 2007 and 2018. As our highway variable is an investment flow measure, the highway change is the sum of the investment flows between 2007 and 2018.

The corresponding first stage equation is given by:

$$\Delta HighwayInvestments_{is} = \beta_4 + \beta_5 CostRelatedIV_{is} + X'_{is}\beta'_6 + \epsilon_{is} \quad (2)$$

Where $CostRelatedIV_{is}$ is our cost-related IVs. We start by analyzing first stage regressions for our econometric specification using GDP as dependent variable and discuss identification in more details. In column 1 we include all cost-related IVs together.

5.2.1. Baseline estimations

The first stage regressions in Table 2 show that most part of the cost-related IVs are strong predictors of the long-term changes in the municipal-level national highway investments (see the KP Wald F Statistics). We observe some non-significant instruments (forest area, water mass and population density) and a small Hansen J p-value suggesting overidentifying issues – probably coming from the non-significant and redundant IVs. Related to the forest area and water mass IVs, we believe that its non-significance could be because Brazil is a country containing large forest areas and water mass, in the sense that such IVs may be too generic to explain any variation in road investments. In the case of population density, the non-significance comes from its high correlation with the urban infrastructure measure.

In column 2 we exclude the variables presenting non-significant parameters in the previous estimation. All parameters remain significant, but the Hansen J test points to overidentifying problems. We then investigate the reason of this issue. Our main suggestion is the inadequacy of the altitude variable – at least as it is measured, being the municipal average altitude – as an IV. Geography variables as average altitude and area are used as controls in income equations as ours to capture the direct geography impact (through agricultural productivity, for instance) and the indirect impact (through the institutional quality channel). In our estimations, the direct impact seems to be non-negligible – whether it occurs, geography affects both income and highway investments, and omitted variable bias is expected.

In column 3 we exclude altitude in the first stage regression, and in column 4 we include altitude as an additional control. In both specifications the Hansen J p-value is bigger than 0.10, suggesting that the instruments are exogenous. In column 4, altitude is proven to be a strong predictor of GDP. The highway investment coefficient seems to be underestimated in the absence of this control, suggesting a slight omitted variable bias. The sloped area IV remains a strong predictor of highway investments. Then, we include altitude as a control in all subsequent models.

This result places a warning about the use of the average altitude measure as an IV in studies about infrastructure and development in underdeveloped countries like Brazil. On the other hand, our preferred measure (sloped area) is the proportion of hilly areas in relation to the total municipal area, which means that even municipalities located in high average altitude areas might have a large proportion of their area geographically suitable for road investments at lower cost. The differences between these two geographical variables can be seen in the far from high correlation (0.18) between them (Figure 5), suggesting that they are predicting geographical issues quite distinctly.

Table 2. Federal Highway Investments and Municipal GDP Growth, 2007-2018: 2SLS IV Regressions

	1	2	3	4	5	6	7	8
Second-stage								
Log Highways Investments	0.0048***	0.0047***	0.0105***	0.0116***	0.0126***	0.0126***	0.0095***	0.0094***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
First-stage								
Legal Protected Areas	0.1645***	0.1742***	0.1852***	0.1742***	0.1863***			
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)			
Environmental Embargos	0.1242**	0.1356**	0.1477***	0.1356**		0.1537***		
	(0.05)	(0.05)	(0.05)	(0.05)		(0.05)		
Forest Area	0.0710							
	(0.07)							
Urban Infrastructure	0.2748*	0.2213**	0.2179**	0.2213**	0.2278**	0.2322***		
	(0.15)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)		
Populational Density	-0.0550							
	(0.15)							
Sloped Area	-0.2484***	-0.2246***	-0.2594***	-0.2246***	-0.2187***	-0.1931***	-0.2656***	
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	
Altitude	-0.3935***	-0.3839***						
	(0.06)	(0.06)						
Water Mass	0.0168							
	(0.06)							
Environmental PCA (excluding Forest Area)							0.1910**	
							(0.09)	
Expropriation PCA							0.3419***	
							(0.07)	
Cost-Related								0.4083***
								(0.12)
Observations	5305	5460	5460	5460	5460	5460	5460	5305
KP Wald F Statistic	10.707	17.317	11.979	10.349	11.911	9.466	15.442	11.283
Hansen J p-value	0.000	0.000	0.174	0.289	0.402	0.230	0.268	

All regressions include the following set of control variables: initial (2007) value of GDP; state fixed effects; municipality area; exports by municipality (% total); rural credit per capita; distance to the nearest federal road; distance to the nearest state road; distance to the nearest port; distance to the nearest railroad; homicide rate; Gini Index; higher education (% population); employment; agriculture share (% GDP); traffic intensity on federal highways; number of railway stations in 1920. Columns 4 to 8 also include Altitude as a control. Robust standard errors reported in parentheses. * 0.1 ** 0.05 *** 0.01.

Next, we try some additional specifications alternating the environmental IVs. Column 5 uses only legal protected areas, whilst Column 6 include only environmental embargos as environmental cost IV. In both specifications the highway investment parameter remains almost unchanged, and the two environmental IVs are good predictors for highway investments. In the case of the environmental embargos, the KP Wald F Statistic is slightly smaller than 10 (the commonly used cutoff).

Finally, as the different cost types have different numbers of IVs – which in turn have different levels of correlation –, we also try some indexes representing each of the cost types. In column 7, geographical costs are captured by the sloped area IV as this variable was the suitable one for this type of cost. Environmental costs are measured as the average of the legal protected area and environmental embargos IVs[1]. Expropriation costs are measured as the average of the urban infrastructure and population density IVs. Result show that this strategy is strong at predicting highway investments in the first stage, whilst it maintains the highway investment parameters almost unchanged in the second stage. In the column 8 we include a single cost related IV measured as the average of the sloped area, the expropriation index, and the environmental index. The cost-related index IV is a good predictor of highway investment as well. However, the smaller KP Wald F Statistic in comparison to column 7 casts some doubt on the aggregated indicator and seems to indicate that the variables capture quite distinct aspects of the infrastructure projects costs.

The environmental IVs positively affect federal highway investments. This result was expected as more environmental costly places might demand a higher level of investments. Similarly, the higher the expropriation cost, the higher the value of investments in federal highways tends to be. On the other hand, geographical costs negatively affect highway investments. One possible explanation is that geographic costs can be more easily predicted from engineering studies in the design phase of the infrastructure project, for example. In this sense, its negative sign represents the fact that these regions are being avoided. On the other hand, expropriation costs have a highly unpredictable aspect as they are impacted by legal disputes involving people. In the same way, environmental costs might raise additional bureaucracy due to environmental licenses not initially planned in the infrastructure projects, as well as lead to new legal disputes involving native populations claiming for their rights on legally protected areas.

Regarding the signal and magnitude of the highway investment parameter in the second stage, it corroborates an extensive number of previous studies which found a positive highway investment impact on local outcomes. Our highway investment elasticity between 0.0048 and 0.0126 is in the range between 0 and 0.06 stablished by Foster et al. (2023b) based on a huge number of infrastructure econometrics studies. In this study, the average elasticity for the transportation sector is 0.03, which brings our estimates even closer.

Now, we turn to our main issues: endogeneity bias. We can ask some questions. First, is there any bias? And second, how is the magnitude of such bias? To answer these questions, we compare our estimates with OLS estimates (see Table A6 in Appendix A). The OLS estimates of the model with the full set of controls returned a highway investment elasticity of 0.0004. The highway investment elasticity estimated using the IV identification strategy is around 0.01. Our results suggest a high underestimation bias in OLS regressions.

To better illustrate the bias, we calculate the return rate to highway investment in Brazil comparing the OLS and 2SLS estimates. To do so, we follow the equation below:

$$RR = \beta_1 * \frac{GDP}{Highway\ Stock} \quad (3)$$

Where RR is the return rate to highway investment, β_1 is the elasticity, GDP is the national GDP and Highway Stock measures in monetary terms how much the highway infrastructure stock is worth. As a proxy for the highway stock, we follow Medeiros, Ribeiro and Amaral (2021) and use the infrastructure estimation by Frischtak and Mourão (2017). The study provides a road stock of R$ 400 billion in values

[1] To be comparable, we standardized the two IVs first. The same procedure is made for the expropriation index and the cost-related index.

corrected by the Consumer Price Index (IPCA). The Brazilian GDP is around R$ 9.9 trillion, implying a GDP/Highway Stock rate of approximately 24.8.

Using the OLS highway elasticity, we generate an underestimated RR of 1.0%. In contrast, using the 2SLS estimates based on the cost-related IVs identification strategy, we calculate a RR of 24.8%. While the methodology and data are different and making a full comparison between studies is impossible, our calculated RR is in line with those ones calculated by Li and Chen (2013), Li et al. (2017) and Wang, Wu, and Feng (2020) for the Chinese case, and Medeiros, Ribeiro and Amaral (2021) for the Brazilian case. The higher magnitude of our RR in comparison with Medeiros, Ribeiro and Amaral (2021) – who found an RR between 17.2% and 22.1% – is expected as we work in a more aggregated (municipal) setting.

5.2.2. Robustness checks

In this Section, we present a number of robustness checks to our main results above. First, we try other commonly used dependent variables. Second, we try a dummy measure of road infrastructure, indicating whether a municipality has received or not highway investments. Third, we discuss other potential sources of endogeneity and try a number of additional IVs. The regressions are not reported in the paper, but they can be obtained upon request.

First, we estimate the federal highway investments impact on GDP per capita, employment and wages. This test is important to validate our empirical strategy and to confirm the highway investment influence on local outcomes. We use the econometric specifications in columns 7 and 8 of Table 2 and apply it to each one of the dependent variables. For all tested dependent variables, the cost-related IVs are good predictors for national highway investments, being suitable in all econometric tests. Also, the signal and significance of the first stage coefficients remained equal. Our results suggest that our identification strategy is suitable not only for the GDP variable, but that it may also be suitable for predicting the highway investments impacts on several other local outcomes.

Second, we also try a dummy measure of infrastructure. A number of studies correctly argues that monetary variables - such as the investment flows used in our study - can contain several measurement errors (Calderón and Servén, 2014; Straub, 2011). Here, we correct (or alleviate) those measurement errors by using an identification strategy including the main infrastructure project costs. Conditional on controls, we argue that these measurement errors coming from spending inefficiency, bureaucracy and so forth, are fixed as we instrument our highway investment variable for critical determinants of infrastructure projects costs. Unreported estimates corroborate our main results and indicate that receiving a highway investment positively affects GDP growth.

Finally, we test a number of IVs related to historical and planned roads in Brazil, following an extensive strand of literature on infrastructure described in Figure 1. We also apply the inconsequential unit approach. First and second stage results remain unchanged, increasing the reliability of our identification strategy.

6. CONCLUDING REMARKS

In this paper, we proposed a new identification strategy based on the main infrastructure costs and a new dataset of national highway investments at the municipal level. We investigated the highway investments impact on several local (municipal) outcomes using which we called cost-related IVs to overcome measurement error and omitted variables bias from the infrastructure measure.

Using our cost related IVs identification strategy, we found highway investment elasticities consistent with a wide range of empirical studies on infrastructure. Results are robust to a number of robustness checks. Also, results seem to suggest a high underestimation bias in OLS regressions. Based on our preferred model, we calculate a return rate to highway investment of 24.2% in Brazil, indicating a (expected) high rentability of this infrastructure.

Future research should focus on longitudinal data. It would allow researchers to include IVs related to demand costs (such as unexpected variations in traffic projections) and input costs (such as unexpected variations in asphalt costs projections). Second, future investigations might focus on the efficiency of highway investments combining monetary data as used in this study with physical road measures.

7. REFERENCES

Adler, M. W., Pasidis, I., Levkovich, O., Lembcke, A. C., & Ahrend, R. (2020). Roads, market access and regional economic development.

Albalate, D., Bel i Queralt, G., Fageda, X., & Geddes, R. R. (2016). The desired and undesired effects of infrastructure and transport policy reforms: An introduction. Case Studies on Transport Policy, 2016, vol. 4, num. 2, p. 168-169.

Aschauer, D. A. (1989). Does public capital crowd out private capital?. Journal of monetary economics, 24(2), 171-188.

Asher, S., & Novosad, P. (2020). Rural roads and local economic development. American economic review, 110(3), 797-823.

Barzin, S., D'Costa, S., & Graham, D. J. (2018). A pseudo–panel approach to estimating dynamic effects of road infrastructure on firm performance in a developing country context. Regional Science and Urban Economics, 70, 20-34.

Baum-Snow, N. (2007). Suburbanization and transportation in the monocentric model. Journal of Urban Economics, 62(3), 405-423.

Baum-Snow, N., Brandt, L., Henderson, J. V., Turner, M. A., & Zhang, Q. (2017). Roads, railroads, and decentralization of Chinese cities. Review of Economics and Statistics, 99(3), 435-448.

Baum-Snow, N., Henderson, J. V., Turner, M. A., Zhang, Q., & Brandt, L. (2020). Does investment in national highways help or hurt hinterland city growth?. Journal of Urban Economics, 115, 103124.

Bird, J., & Straub, S. (2020). The Brasilia experiment: the heterogeneous impact of road access on spatial development in Brazil. World Development, 127, 104739.

Brooks, L., & Liscow, Z. (2023). Infrastructure costs. American Economic Journal: Applied Economics, 15(2), 1-30.

Calderón, C., & Servén, L. (2014). Infrastructure, growth, and inequality: An overview. World Bank Policy Research Working Paper, (7034).

Chandra, A., & Thompson, E. (2000). Does public infrastructure affect economic activity?: Evidence from the rural interstate highway system. Regional science and urban economics, 30(4), 457-490.

Coşar, A. K., & Demir, B. (2016). Domestic road infrastructure and international trade: Evidence from Turkey. Journal of Development Economics, 118, 232-244.

Cosci, S., & Mirra, L. (2018). A spatial analysis of growth and convergence in Italian provinces: the role of road infrastructure. Regional Studies, 52(4), 516-527.

Duranton, G., Morrow, P. M., & Turner, M. A. (2014). Roads and Trade: Evidence from the US. Review of Economic Studies, 81(2), 681-724.

Duranton, G., & Turner, M. A. (2012). Urban growth and transportation. Review of Economic Studies, 79(4), 1407-1440.

Faber, B. (2014). Trade integration, market size, and industrialization: evidence from China's National Trunk Highway System. Review of Economic Studies, 81(3), 1046-1070.

Farhadi, M. (2015). Transport infrastructure and long-run economic growth in OECD countries. Transportation Research Part A: Policy and Practice, 74, 73-90.

Fedderke, J. W., & Bogetić, Ž. (2009). Infrastructure and growth in South Africa: Direct and indirect productivity impacts of 19 infrastructure measures. World Development, 37(9), 1522-1539.

Frye, D. (2016). Transportation networks and the geographic concentration of employment.

Foster, V., Gorgulu, N., Jain, D., Straub, S., & Vagliasindi, M. (2023a). The Impact of Infrastructure on Development Outcomes: A Qualitative Review of Four Decades of Literature.

Foster, V., Gorgulu, N., Jain, D., Straub, S., & Vagliasindi, M. (2023a). The Impact of Infrastructure on Development Outcomes: A Meta-Analysis

Garcia-López, M. À., Holl, A., & Viladecans-Marsal, E. (2015). Suburbanization and highways in Spain when the Romans and the Bourbons still shape its cities. Journal of Urban Economics, 85, 52-67.

Ghani, E., Goswami, A. G., & Kerr, W. R. (2016). Highway to success: The impact of the Golden Quadrilateral project for the location and performance of Indian manufacturing. The Economic Journal, 126(591), 317-357.

Gertler, P. J., Gonzalez-Navarro, M., Gracner, T., & Rothenberg, A. D. (2016). Road Quality, Local Economic Activity, and Welfare: Evidence from Indonesia's Highways.
Herzog, I. (2021). National transportation networks, market access, and regional economic growth. Journal of Urban Economics, 122, 103316.
Holl, A. (2016). Highways and productivity in manufacturing firms. Journal of Urban Economics, 93, 131-151.
Hsu, W. T., & Zhang, H. (2014). The fundamental law of highway congestion revisited: Evidence from national expressways in Japan. Journal of urban economics, 81, 65-76.
Huang, Y., & Xiong, W. (2017). Geographic Distribution of Firm Productivity and Production: A ", Market Access" Approach. Working Paper.
Jaworski, T., & Kitchens, C. T. (2019). National policy for regional development: Historical evidence from Appalachian highways. Review of Economics and Statistics, 101(5), 777-790.
Ke, X., & Yan, Y. (2021). Can proactive fiscal policy achieve the goal of "Beyond Keynesianism"? Evidence from China's National Highway System. Review of Development Economics, 25(2), 1078-1103.
Kenny, C. (2009). Measuring corruption in infrastructure: Evidence from transition and developing countries. The Journal of Development Studies, 45(3), 314-332.
Li, Z., Wu, M., & Chen, B. R. (2017). Is road infrastructure investment in China excessive? Evidence from productivity of firms. Regional Science and Urban Economics, 65, 116-126.
Lu, H., Zhao, P., Hu, H., Zeng, L., Wu, K. S., & Lv, D. (2022). Transport infrastructure and urban-rural income disparity: A municipal-level analysis in China. Journal of transport geography, 99, 103292.
Martincus, C. V., Carballo, J., & Cusolito, A. (2017). Roads, exports and employment: Evidence from a developing country. Journal of Development Economics, 125, 21-39.
Martín-Barroso, D., Núñez-Serrano, J. A., & Velázquez, F. J. (2015). The effect of accessibility on productivity in Spanish manufacturing firms. Journal of Regional Science, 55(5), 708-735.
Medeiros, V., Ribeiro, R. S., & AMARAL, P. (2021a). Productivity of transportation infrastructure in Brazil: a sectoral and regional approach using dynamic panel data models. Coletânea de Trabalhos– Prêmio ABDE-BID: edição.
Medeiros, V., de Queiroz Stein, A., Ribeiro, R. S. M., & dos Santos, U. P. (2021b). Transportation infrastructure and University-Industry collaborations: regional-level evidence from Brazil. Cambridge Centre for Economic and Public Policy, Department of Land Economy, University of Cambridge.
Meijers, E., Hoekstra, J., Leijten, M., Louw, E., & Spaans, M. (2012). Connecting the periphery: Distributive effects of new infrastructure. Journal of Transport Geography, 22, 187-198.
Michaels, G. (2008). The effect of trade on the demand for skill: Evidence from the interstate highway system. The Review of Economics and Statistics, 90(4), 683-701.
Percoco, M. (2016). Highways, local economic structure and urban development. Journal of Economic Geography, 16(5), 1035-1054.
Redding, S. J., & Rossi-Hansberg, E. (2017). Quantitative spatial economics. Annual Review of Economics, 9, 21-58.
Redding, S. J., & Turner, M. A. (2015). Transportation costs and the spatial organization of economic activity. Handbook of regional and urban economics, 5, 1339-1398.
Roberts, M., Melecky, M., Bougna, T., & Xu, Y. (2020). Transport corridors and their wider economic benefits: A quantitative review of the literature. Journal of Regional Science, 60(2), 207-248.
Rokicki, B., & Stępniak, M. (2018). Major transport infrastructure investment and regional economic development–An accessibility-based approach. Journal of Transport Geography, 72, 36-49.
Sheard, N. (2014). Airports and urban sectoral employment. Journal of Urban Economics, 80, 133-152.
Souza Jr, C. M., Z. Shimbo, J., Rosa, M. R., Parente, L. L., A. Alencar, A., Rudorff, B. F., ... & Azevedo, T. (2020). Reconstructing three decades of land use and land cover changes in brazilian biomes with landsat archive and earth engine. Remote Sensing, 12(17), 2735.
Storeygard, A. (2016). Farther on down the road: transport costs, trade and urban growth in sub-Saharan Africa. The Review of economic studies, 83(3), 1263-1295.

Straub, S. (2008). Infrastructure and growth in developing countries: recent advances and research challenges. World Bank policy research working paper, (4460).
Straub, S. (2011). Infrastructure and development: A critical appraisal of the macro-level literature. The Journal of Development Studies, 47(5), 683-708.
Xu, M. I. N. G., & Feng, Y. U. A. N. (2022). How transportation infrastructure affects firm Productivity? Evidence from China. China Economic Quarterly International, 2(1), 55-69.
Wang, Z., Wu, G. L., & Feng, Q. (2020). Productivity of core infrastructure investment in China: An input–output approach. The World Economy, 43(12), 3384-3406.
Yang, Y. (2018). Transport infrastructure, city productivity growth and sectoral reallocation: Evidence from China. International Monetary Fund.
Zhang, X., Hu, Y., & Lin, Y. (2020). The influence of highway on local economy: Evidence from China's Yangtze River Delta region. Journal of Transport Geography, 82, 102600.
Zhang, Y. F., & Ji, S. (2019). Infrastructure, externalities and regional industrial productivity in China: A spatial econometric approach. Regional Studies.