Productivity of transportation infrastructure in Brazil: a sectoral and regional approach using dynamic panel data models

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Abstract: We assess the productivity of highway infrastructure using sectoral data by state between 2007 and 2017 in Brazil. We apply dynamic panel data models considering cross-sector variation in infrastructure reliance, which allows us to consistently treat endogeneity issues between infrastructure and productivity. Our main findings point out that sectors more dependent on road infrastructure benefited more from road expanding in Brazil. Based on our preferred model, we find an annual economic return rate to road investment in Brazil around 22%, thus providing an important measure of infrastructure investment rentability. To reduce our rate of return to the threshold of 8.5% based on the social discount rate, Brazil would need 2.6 times more highways, which implies a road stock of around 16% of the national GDP.

Resumo: Esse artigo avalia a produtividade da infraestrutura rodoviária usando dados setoriais por estado entre 2007 e 2017 no Brasil. A partir de modelos de dados de painel dinâmicos, considerando a variação intersetorial na dependência à infraestrutura, trata-se problemas de endogeneidade entre infraestrutura e produtividade. Os principais resultados apontam que setores mais dependentes da infraestrutura rodoviária se beneficiaram mais com a expansão rodoviária no país. Os resultados indicam uma taxa de retorno econômico anual para o investimento em rodovias em torno de 22%, constituindo uma medida importante da rentabilidade do investimento em infraestrutura. Para reduzir tal taxa de retorno ao patamar de 8,5% com base na taxa social de desconto, o Brasil precisaria de 2,6 vezes mais rodovias, o que implica um estoque de rodovias em torno de 16% do PIB nacional.

Keywords: transportation infrastructure; productivity; Brazil.

Palavras-chave: infraestrutura de transportes; produtividade; Brasil.

JEL Codes: H54; O18; O47.

Área 6 - Crescimento, Desenvolvimento Econômico e Instituições

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Abstract

The road sector is historically seen as one of the main bottlenecks of the Brazilian economy and it is currently a central theme of wide debates around national and regional public policies. We assess the productivity of highway infrastructure using sectoral data by state between 2007 and 2017 in Brazil. We apply dynamic panel data models considering cross-sector variation in infrastructure reliance, which allows us to consistently treat endogeneity issues between infrastructure and productivity. Our main findings point out that sectors more dependent on road infrastructure benefited more from road expanding in Brazil. Based on our preferred model, we find an annual economic return rate to road investment in Brazil around 22%, thus providing an important measure of infrastructure investment rentability. To reduce our rate of return to the threshold of 8.5% based on the social discount rate, Brazil would need 2.6 times more highways, which implies a road stock of around 16% of the national GDP.

1. Introduction

A vast empirical literature has examined the productivity returns of infrastructure investments worldwide. Since Aschauer (1989), several studies have largely identifying positive returns of infrastructure on productivity (Arbués, Baños and Mayor, 2015; Calderón, Moral-Benito and Servén, 2014; Cohen, 2010; Fedderke and Bogetić, 2009; Munnell, 1992)[1]. This main finding has deeply influenced policymakers, pointing out that expanding and improving infrastructure stimulates economic activity in the short run through the expansion of investments in construction of new assets as well as in the medium and long run by raising labor and capital productivity growth rates. Billionaire infrastructure spending packages have been proposed in the United States, Europe, and Asia to overcome the health and economic global crisis caused by Covid-19, influencing infrastructure policies around the globe.

However, a more careful look at theoretical and methodological issues shows that the mechanisms through which infrastructure affects economic development are not as clear as they seem to be (Calderón and Servén, 2014; Redding and Turner, 2015; Straub, 2011). A critical issue in empirical studies on infrastructure – using cross-country data, country time series data or even regional data – is the absence of a sectoral approach. Economic sectors respond differently to infrastructure investments and, as locations produce different goods and services, they may respond

[1] For a more detailed literature review on this topic see, for example, Melo, Graham and Brage-Ardao (2013).

heterogeneously to infrastructure expansion and improvement (Fernald, 1999; Holl, 2016; Li et al., 2017; Percoco, 2016; Wang, Wu and Feng, 2020).

Another relevant issue refers to the fact that a relevant part of infrastructure literature neglects deep complexities about the relationship between infrastructure and economic development at the regional scope. Investments in infrastructure are spatial in nature, as it involves competing choices regarding the location of structures and equipment that serve limited geographic areas (Behrens et al., 2007; Elburz, Nijkamp and Pels, 2017; Faber; 2014; Fingleton and Szumilo, 2019). The stock and quality of roads affect the preferences of companies and families and, as they are distributed asymmetrically across locations, they will decisively influence decisions on the location of agents, such as migration, installation of new companies, capital investment in different places and so forth. In this context, the transmission channels of infrastructure investments on productivity and growth become much more complex and less intuitive in a scenario of deep regional and income disparities as in the Brazilian case (Medeiros and Ribeiro, 2020; Medeiros, Ribeiro and Amaral, 2021).

We assess the sector-level productivity of road infrastructure by state between 2007 and 2017 in Brazil. Our sample has 65 sectors inserted into each one of the 27 Brazilian states. This period was characterized by two simultaneous and important facts, which makes the Brazilian case interesting. First, the Growth Acceleration Program (PAC) (2007-2018) of the Federal Government, aimed at promoting economic growth and employment, substantially increased spending on transport infrastructure in the country. Second, we observe a period of relatively high productivity growth (up to 2015) based on low-tech sectors and commodity exports (Nassif et al., 2015). In this way, our case study differs from all the previous studies using the infrastructure reliance approach by estimating the productivity of infrastructure investment in an early deindustrialization country (Rodrik, 2016).

Our empirical approach intends to overcome two main issues. Firstly, we include the infrastructure reliance of each sector in the model following Fernald (1999), Li and Li (2013), Li et al. (2017), Percoco (2016) and Wang, Wu and Feng (2020). This procedure seeks to assess more accurately the sectoral productivity gains following road investment. Secondly, we use dynamic panel data models in order to estimate how current sectoral productivity growth depends on its past observations. Our approach is novel as it allows us to differentiate short and long run impacts of road investment on sectoral productivity. Thirdly, to ensure the exogeneity condition between infrastructure and productivity, we also advance in the literature by proposing the use of a number of external instruments for the Brazilian case based on planned roads, expected budget and budget effectiveness, and infrastructure projects costs. We also contribute to the empirical literature on infrastructure and productivity by explicitly including a physical measure of road quality in the model. Thereby, we control for the marked heterogeneity in terms of quality of the state-level road network in Brazil, by providing estimates robust to measurement errors.

Our main findings point out that sectors more dependent on road infrastructure benefited more from road investment in Brazil. Our main estimates show that the average sectoral productivity elasticity of highway investment is 0,006, which is in line with previous studies (Li *et al.*, 2017; Wang, Fu ang Weng, 2020). These results remain under several specifications controlling for endogeneity issues, road quality, regional heterogeneity, and outliers. We also find an increasing of 29% in the productivity elasticity of infrastructure in the long-run compared to the short-run, proving the broad discussed long-run characteristic of infrastructure investment. Based on our preferred models and on Frischtak and Mourão's (2017) road stock estimates, we find an economic return rate to road investment in Brazil around 22%, thus providing an important measure of infrastructure investment rentability.

The paper has three sections in addition to this introduction. Chapter 2 describes the methodological problems and our treatment and estimation proposals. Chapter 3 displays the results and further discussions. Finally, we conclude.

2. Empirical approach

2.1. Econometric specification

To estimate the infrastructure returns on productivity, we rely on Fernald (1999), Li et al. (2017) and Wang, Wu and Feng (2020). The model formalizes that those industries that are more dependent on road infrastructure should experience a greater change in productivity caused by an expansion or improvement in the highway network.

Fernald (1999) proves that the productivity of an industry j is a function of road investment and industry-specific elasticity. In this framework, a pivotal role is played by the technological linkages between sectors (Percoco, 2016), which can be calculated by a measure capturing the infrastructure dependence of each sector (φ_j). As the distribution of sectors may be different across states, one can calculate the state aggregate elasticity ξ_s by taking the weighted average of the share of each industry by state as follow:

$$\xi_s = \alpha_1 * \sum_j \varphi_j * \omega_{js} \qquad (1)$$

Where ω_{js} is the value added of industry j in state s, and α_1 is the estimated effect of road infrastructure on productivity. Following Wang, Wu and Feng (2020) and applying it to sector-level data, the annual return rate to road investment can be approximated as follows:

$$R = \sum_s \xi_s * \theta_s * \frac{Y_s}{G_s} \qquad (2)$$

where Y_s is the aggregate value added of all sectors by state, G_s is the value of the road stock of each state and θ_s is the state's GDP as proportion of the national GDP. To generate α_1, we construct the following initial econometric specification:

$$Y_{jst} = \alpha_0 + \alpha_1 * \varphi_j * Highways(Stock)_{st} + \beta' Controls_{jst} + \varepsilon_{jst} \qquad (3)$$

where Y_{jst} is the productivity by sector, $Highways(Stock)_{st}$ is the stock of highways by state, $Controls_{jst}$ is a vector of control variables, j represents the sectors, s is the state, t is the year, α_0 is a constant term, and ε_{jst} the idiosyncratic error term. We are interested in α_1, which measures the road investment effect on productivity, while β' is a vector of parameters of the control variables. When α_1 is positive, it implies that infrastructure investment is productive, and sectors that dependent more on road infrastructure gain more benefit from road investment (Li *et al*., 2017). We control for time fixed effects to avoid specific shocks over time. We also include state fixed effects to control for state idiosyncratic shocks as well as differential price levels and local economic policies.

An addition we made from previous literature is the inclusion of an explicit measure of road quality. From (3), we include road quality as follow:

$$Y_{jst} = \alpha_0 + \alpha_1 * \varphi_j * Highways(Stock * Quality)_{st} + \beta' Controls_{jst} + \varepsilon_{jst} \qquad (4)$$

In (4), $Highways(Stock * Quality)_{st}$ captures both road stock and quality. Equation (4) allows us to effectively capture productivity effects of both the expansion of new roads and improvements in the existing network.

2.2. Identification issues

To estimate the causal impact of infrastructure on productivity using equation (4), we need to solve several potential endogeneity issues. The first problem is related to reverse causality between infrastructure investment and productivity at the state level. Governments may be interest in attending regions that are expected to growth more or developing backward regions to promote regional balanced economic growth. Thus, productivity levels and growth matters to the allocation of highway investment, and our initial specification suffers from reverse causality.

The second issue is related to omitted variable bias. Several sector, state and country time-varying factors may shape the sector productivity growth and infrastructure allocation simultaneously (Fernald, 1999). Macroeconomic and sectoral shocks, as well as local economic policies are examples of such potential factors. If it occurs, the coefficients may be biased.

Finally, one can observe a dependent process where the productivity of a sector in the current period are highly based on its past productivity. This is relevant in developing countries as Brazil, where one can observe a significant process of path dependence in which some firms, sectors, or regions - due to several productive, institutional and infrastructure constraints - are unable to growth and develop. A way to deal with this temporal dynamic is by including past periods of the dependent variable in the model. However, it generates another source of endogeneity coming from the current and past value of productivity.

2.3. The dynamic panel data model

To estimate the temporal dynamic and the causal impact of highway investment on sector-level productivity, we start by including an autoregressive term in (3) and (4) as follows:

$$Y_{jst} = \alpha_0 + \gamma * Y_{jst-1} + \alpha_1 * \varphi_j * Highways(Stock)_{st} + \beta' * Controls_{jst} + \varepsilon_{jst} \quad (5)$$

$$Y_{jst} = \alpha_0 + \gamma * Y_{jst-1} + \alpha_1 * \varphi_j * Highways(Stock * Quality)_{st} + \beta' * Controls_{jst} + \varepsilon_{jt} \quad (6)$$

Note that conditional on lagged sector-level productivity Y_{jst-1}, the correlation between current sector-level productivity Y_{jst} and state level highway investment is the effect of infrastructure investment on productivity growth, which is in line with de elasticities calculated by Fernald (1999), Li et al. (2017) and Wang, Wu and Feng (2020).

To overcome the endogeneity issues described so far, the GMM-Difference and the GMM-System techniques for panel data are suitable (Arellano and Bond,1991; Arellano and Bover, 1995; Blundell and Bond, 1998). This methodology is appropriate for our exercise as it avoids possible endogeneity issues of one or more regressors, controls for specific non-observed effects of the cross-section units and allows the panel to be dynamic by inserting lagged values of the dependent variable as explanatory variables of the model. The GMM estimators are based on regressions in differences and utilize instruments to control endogeneity.

To solve the endogeneity problem, Arellano and Bond (1991) proposed a method subtracting the average of all available future observations of a variable. Thereby, the method is applicable for all observations, except the last of each individual, minimizing the loss of data independently of the number of lags. Since the lagged variables do not fit into the formula, they can be used as instruments. However, lagged variables may be weak instruments for the first differences. This occurs especially in the case where the variables present a high degree of persistence over time, as is the case of productivity. To overcome this issue, the GMM-System (Arellano and Bover, 1995; Blundell and Bond, 1998) can be used, as it differentiates the instruments themselves to make them exogenous to the fixed effects. The solution occurs by including the lagged differences of the endogenous variables as instruments of the same variables in level in the model, the GMM-System.

By applying the proposed model, we solve the problem of endogeneity between current and past values of productivity as well as unobserved fixed effects bias. Nevertheless, the endogeneity coming from nonrandom investment allocation may remain even instrumenting the model with internal instruments. To solve the endogeneity of infrastructure itself, we construct a broad and novel set of external instrumental variables based on government budget, environmental costs, and local demand for infrastructure literature (Coşar and Demir, 2016; Duranton and Turner, 2012; Duranton et al., 2014; Gertler et al., 2019; Medeiros et al., 2021; Percoco, 2016), considering the Brazilian case. By combining the internal instruments approach proposed by the GMM-System model with external instruments based on the infrastructure literature, we can estimate the causal effect of infrastructure on productivity.

2.4. External instruments

A key point in our empirical approach is to find suitable external instruments for highway investment. To attend the empirical requirements, the external instruments need to influence the productivity growth only through road investment, conditional on control variables. We then propose six external instruments based on three different predictors of highway network and investments: i) planned roads or planned budget; ii) demand for infrastructure, and iii) infrastructure project costs (Duflo and Pande, 2007; Gertler et al., 2019; Medeiros et al., 2021; Redding and Turner, 2015; Wang et al., 2018).

The first instrument we propose is the length of Federal Government planned roads by state and year. Federal Government are more able to articulate national and regional infrastructure policies aiming at enlarging country connectivity and access to external markets. It is less likely that major federal road corridors seek to expand specific sectors in particular states. Similarly, as federal policies are independent of the states, temporal variation in federal road budget is plausibly exogenous to changes in state economic activity. Then, we use the expected budget of the Federal Government in the transportation sector by year as another instrument (Gertler et al., 2019). These variables are good predictors of physical roads as they are planned but has no direct effect on productivity as they do not exist yet.

Next, we construct an indicator of Federal Government budget effectiveness, measured as the degree of budget execution (investments effectively paid in relation to total planned investments) by year. Whilst this variable has the potential to harm an infrastructure project by incurring in execution delays or discontinuity, we have no reasons to claim that it will affect sector-level productivity growth directly in a specific state, but only through the realization (or not) of an infrastructure investment.

The second and third set of variables are based on the cost structure of infrastructure projects in Brazil. When elaborating a public road project, authorities need to elaborate studies considering the demand for infrastructure that the project are expected to cover as well as environmental, expropriation and geographical costs. Projects will be done and lately be feasible depending on whether it is highly socially or productively demanding and/or economically profitable. We use two variables to represent the propensity of a state to receive highway investments. The first one is the number of deaths per 100 traffic accidents in 2007 in federal government roads, the initial year of the PAC. Similarly, we test the number of traffic accidents per 100km of roads in 2007 in federal government roads. The first one captures the severity of traffic accidents, whilst the second one represents the intensity of accidents[2]. The higher the number of accidents or deaths in traffic the higher tends to be the priority of a state to receive an infrastructure project. Whether these projects will be carried out will depend on factors as public and private resources, federal government planning, financing mechanisms and so forth, which is out of the control of the states.

To cover environmental and geographical costs we use the proportion of legally protected areas[3] in each state as proxy. The greater the proportion of protected areas, the more difficult it may be to constructing highways there. Building highways in legally protected areas, when it is possible, requires incurring in huge bureaucratic costs including environmental licensing and long delays in permitting issuances by local authorities (Medeiros et al., 2021)[4]. We have no reason to argue that protected areas may directly influence sector-level productivity.

Since some variables vary only by year and others by state, we interact them to create instruments at the state-level varying by year (Wang et al., 2018). We then construct five external instruments, totalizing six with the planned Federal Government roads that varies by state and year. The validity of the GMM estimators depends substantially on the degree of exogeneity of the internal and external instruments used in the estimated model. The endogeneity of the instruments can be evaluated by applying the Hansen Test. The null hypothesis implies the joint validity of the instruments. The Arellano and Bond test for AR (2) tests the null hypothesis that the residuals of the difference regression are serially correlated in the second order. Rejection of the null hypothesis suggests that the instruments used are inadequate. Notwithstanding, the use of an excessive number of instruments may cause overidentification issues. We tried to maintain the number of instruments to the minimum following the Roodman (2009) rules. To do so, we have collapsed the instrument matrix to limit the proliferation of the instruments.

2.5. Data

2.5.1. Highway measures and external instruments

[2] It is likely that the severity of accident be a better instrument for road investment, as it is more related to road infrastructure. The intensity of accident may be also correlated with demographic conditions.
[3] These are conservation units (sustainable use and integral protection), military areas and indigenous lands.
[4] National survey demonstrates excessive bureaucracy as one of the main problems in the construction and infrastructure sector - 30.5% of the country's entrepreneurs answered that they spent considerable time and resources in complying with legal requirements to set up, obtain licenses and authorizations) (CNI, 2019).

The first dataset is related to the state-level measures of highway investment. Fernald (1999) and Wang, Wu and Feng (2020) used monetary measures of infrastructure investment to account for both road stock and quality. However, using monetary measures such as investment flows and government expenditure by function may lead to considerable measurement error. Due to inefficiencies in contracts, corruption, as well as implementation failures and other institutional issues, monetary flows do not necessarily translate into effective infrastructure for population use (Medeiros and Ribeiro, 2020; Straub, 2011). This issue is even more problematic in developing countries where the effectiveness of infrastructure investment is dubious. PAC investments were poor in terms of budget effectiveness. While investments grew substantially, budget execution was quite low, causing delays in payments and execution schedules (Raiser et al., 2017). The budget effectiveness may be more related to the current revenue capacity of the government - which in turn depends on the economic activity and other factors - than the physical deliveries of road construction and services. In addition, a relevant share of transport investments in Brazil is made by private agents. In recent years, highway concessions investments have converged to a comparable level in relation to the Federal Government investments (CNT, 2018). In this sense, the use of government investments would represent a low amount of total investments in the sector and could not adequately represent the provision of highway infrastructure in Brazil. Thus, monetary measures may represent inappropriately the transport infrastructure and services that are effectively offered to the population.

We use road length as a proxy for road investment, a widely used variable in developing economies (Baum-Snow et al., 2017; Duranton and Turner, 2012; Duranton et al., 2014; Li et al., 2017; Medeiros, Ribeiro and Amaral, 2021). A great advantage of this variable is that it is much easier to measure than investment flows, and thus reduces measurement errors, specially whether road investment is mainly for construction of new roads (Li et al., 2017). Whilst a relevant part of PAC road investments was directed to road construction, ignoring road improvements and maintenance would constitute a critical bias in our empirical work. Therefore, we construct a novel measure capturing the variation coming from the construction of roads as well its quality.

The first variable used, road length, was obtained from the National Department of Transport Infrastructure (*DNIT*). The second one, road quality, was derived from the CNT Road Survey (*Pesquisa Confederação Nacional do Transporte (CNT) de Rodovias*)[5]. This survey evaluates the road quality in terms of pavement, signaling, geometry and the overall road quality. The roads are classified as bad, poor, regular, good, and great. From the survey, we construct our main[6] road quality measure as follow:

[5] Medeiros, Ribeiro and Amaral (2021) used this survey to generate a similar road quality measure.
[6] We tried several other weights, which will be used later as robustness tests.

$$\text{RoadQuality}_{st} = \frac{1*\text{Roads}_{bad} + 2*\text{Roads}_{poor} + 3*\text{Roads}_{regular} + 4*\text{Roads}_{good} + 5*\text{Roads}_{great}}{\text{Total roads}} \quad (7)$$

Then, we test two measures as proxies for highway investments[7]:

$$Highway(Stock)_{st} = \log(road\ lenght_{st}) \quad (8)$$

$$Highway(Stock * Quality)_{st} = \log(road\ lenght_{st} * RoadQuality_{st}) \quad (9)$$

The third dataset is the national input output table from the Brazilian Institute of Geography and Statistics (IBGE) of 2010. From this table, we can calculate our measure of infrastructure reliance. Following Wang, Wu and Feng (2020), the sector-infrastructure reliance is the share of the value of road investment as intermediate input in a sector to the total intermediate input value of that sector. Differently from previous studies, we include both short and long run infrastructure dependence by sector. The short run term is included by taking the share of the value of the road construction sector as intermediate input in a sector to its total intermediate input value. The long run term is the share of the value of road services as intermediate input in a sector to its total intermediate input value. Which we named long run infrastructure reliance is the common measure used in the literature (Fernald, 1999; Li et al., 2017). We argue that the short run dependence may be important as it stimulates economic activity in the construction phase and may generate effects on productivity as well.

In relation to the external instruments, the length of planned roads and the Federal Government budget in the transportation sector were provided by the Ministry of Infrastructure. The traffic accidents variables were obtained from the Federal Highway Police (*PRF*) database. The protected areas had as source the Ministry of Environment.

2.5.2. Sector-level data

We use the RAIS (*Relação Anual de Informações Sociais*) to construct the measures of productivity and the control variables at the sector level. RAIS are the most complete annual database in Brazil, containing extensive information about the formal labor market. It includes the number of workers and establishments, wages, worked hours, education level, genre, and age disaggregated by sector and regional classifications. As our main objective is to test the infrastructure returns on productivity considering the infrastructure reliance of each sector, this database is the one that allows us to work with the most disaggregated sectorial classification. We merge the sectors in the RAIS database with the 68 sectors in the input output table. Next, we excluded the land transport and construction sectors as they were outliers based on our measure of infrastructure reliance. The public administration sector was also excluded, as it suffers from some

[7] Road length includes both federal and state highways. The federal road series cover the years 2007-2017, while the state road series stops in 2015. We test federal roads isolated and federal plus state roads to give robustness to our results.

issues in RAIS[8]. Then, we keep 65 sectors. By using this dataset, we extend prior empirical exercises evaluating manufacturing sectors by including agriculture, mining, and several services sectors.

Differently from Fernald (1999), Li at el. (2017) and Wang, Wu and Feng (2020), we are not able to construct a total factor productivity (TFP) measure, as we have no capital input information at the firm or sector level. Due to this data issue, we proxy productivity as follow[9]:

$$Productivity_{jst} = \frac{Wages_{jst}}{Worked\ hours_{jst}} \tag{10}$$

We construct several sector level variables as controls. We include the share of women employees, the share of workers with tertiary education, the share of workers by age range and the proportion of large firms by sector. We also construct dummy variables for each one of the great sectors agriculture and mining, manufacturing, and services, as well as for the each one the five OCDE classes based on R&D technological intensity (Galindo-Rueda, and Verger, 2016).

The OCDE classification is relevant in our exercise as it includes agriculture and services sectors, a distinction that had not been made yet in studies on highway investment and productivity using the proposed empirical approach. In Brazil, the sectors of low to medium-low technological intensity are the most intensive in road infrastructure. As expected, the agriculture and mining sectors are those that rely more on transport infrastructure[10].

2.5.3. State-level data

Two control variables at the state level are critical in our specification, specially to mitigate possible omitted variable biases. The first one is the relevance of agriculture sector in the economy of each state. The PAC period coincided with a period of appreciation of the prices of basic products. 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. The lack of this variables would generate a relevant omitted variable bias, then we include the share of agriculture value added in the total value added in a state as control.

Similarly, infrastructure investments are seen as an important determinant of exports performance (Coşar and Demir, 2016; Duranton et al., 2014). Exporting states may have received a

[8] The problem stems from the fact that public companies report information at their headquarters. Therefore, workers from all locations are entered as belonging to a single location. The main issue in RAIS is the omission of declarations by the establishments, followed by an error in filling it out, resulting from incomplete or incorrect information. This problem is more relevant in more informal sector as agriculture and construction.

[9] We can observe a high correlation between labor productivity and TFP measures using Brazilian data (FGV). Similarly, there is a high correlation between wages and GDP in Brazilian states. Whilst we need to be cautious with the differences among the measures, we argue that our dependent variable is a valid proxy to estimate the infrastructure returns on productivity.

[10] All sector and its classifications are available upon request.

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 population density to control for the state size, the ICMS tax[11] as proportion of the state GDP to control for the size of the state government, and the homicide rate as a proxy for institutional quality and level of social development (Medeiros and Ribeiro, 2020; Medeiros, Ribeiro and Amaral, 2021)[12].

3. Results and discussion

3.1. Baseline results

Table 1 shows the baseline results on the productivity effects of an increase in highway infrastructure stocks[13]. This specification captures only the stock component of roads, avoiding the quality measure. In addition to the internal instruments common to the method, we include our six external instruments in the model. All regressions include sector level control variables, which are not reported in the Tables but had the expected signs, year, and state fixed controls. As robustness checks, we have included the control variables at the state level one by one to evaluate whether the road effect remains.

In all regressions, the coefficients of the road investment variable interacted with the infrastructure reliance measure were positive and statistically significant, remaining constant even with the inclusion of several controls. The positive sign of α_1 indicates that federal highway investments are productive. The autoregressive term coefficient was positive and significant, demonstrating that sector productivity in Brazil follows a dynamic process. As expected, the agriculture share has a negative effect on productivity, as agriculture sectors presents lower productivity levels (Nassif et al., 2015). The higher the exports in a state in relation to the national exports the higher is productivity. This result was expected since exporting states are expected to be more competitive, presenting higher levels of productivity. Population density presents a negative sign, indicating that states with more concentrated population had a decreasing in productivity in the period. The other state level controls were not statistically significant. Using column 6 and taking the sample average of φ equal to 0,048, the sector average output elasticity of highway investment is 0,007, in line with Wang, Wu and Feng (2020).

[11] The ICMS is the most relevant state level tax in Brazil, representing about 80% of state revenues.
[12] Descriptive statistics are inserted into a appendix, which is available upon request.
[13] We have also tried a similar measure of productivity, dividing the sector wages by the number of workers. The results were quite the same, then they are not reported. We have also tested infrastructure as an exogenous variable, which seem to underestimate the highway return on productivity.

Table 1. *Highways impact on productivity: endogenous specification*

	1	2	3	4	5	6
Productivity, lagged	0.241***	0.242***	0.242***	0.238***	0.239***	0.238***
	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
Highways* φ	0.142***	0.145***	0.131***	0.142***	0.142***	0.137**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Agriculture share (%GDP)		-0.002	-0.003**	-0.004**	-0.004**	-0.004**
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Exports by State (%Total)			0.957***	0.889***	0.909***	0.905***
			(0.16)	(0.15)	(0.15)	(0.15)
Population Density				-0.001***	-0.001***	-0.001***
				(0.00)	(0.00)	(0.00)
ICMS Tax (%GDP)					0.047	0.059
					(0.05)	(0.05)
Homicide rate						0.000
						(0.00)
Constant	2.318***	2.341***	2.364***	2.401***	2.399***	2.397***
	(0.22)	(0.23)	(0.23)	(0.23)	(0.23)	(0.23)
Observations	18121	18121	18121	18121	18121	18121
Instruments	61	62	63	64	65	66
R^2 Adjusted						
Arellano-Bond test for AR(2) in first difference (p-value)	0.517	0.520	0.528	0.572	0.568	0.565
Hansen test of joint validity of instruments (p-value)	0.208	0.182	0.167	0.177	0.183	0.196

All GMM-System regressions include sector level control variables, State and time fixed effects. Up to the fifth lag of the endogenous variables were used as instruments for the endogenous. Robust standard errors, clustered at the state-year level, are reported in parentheses. * 0.1 ** 0.05 *** 0.01.

Next, we include state level roads in our stock measure. Whilst the federal roads cover all the period 2007-2017 and are less affected by endogeneity issues, state government roads are an important source of flows of cargo and people within states. For instance, São Paulo has an extensive state-level concession program, while the federal road stock in São Paulo is not so large relatively to other states. Therefore, we test the productivity of the overall road stock (the sum of federal and state roads) in the period 2007-2015. Table 2 shows the results.

Table 2. *Highways impact on productivity: endogenous specification including state highways*

	Planned roads	Protected areas * Budget effectivenes s	Protected areas * Expected budget	Deaths per 100 traffic accidents in 2007 * Expected budget	Traffic accidents by 100 km of roads in 2007 * Expected budget	Planned roads * Budget effectiveness	All instruments
Productivity, lagged	0.202***	0.195***	0.194***	0.196***	0.199***	0.220***	0.228***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Highways* φ	0.160***	0.160***	0.160***	0.157***	0.157***	0.157***	0.149***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Observations	14838	14838	14838	14838	14838	14838	14838
Instruments	59	59	59	59	59	59	64
R^2 Adjusted							
Arellano-Bond test for AR(2) in first difference (p-value)	0.476	0.510	0.519	0.505	0.497	0.392	0.355
Hansen test of joint validity of instruments (p-value)	0.111	0.251	0.255	0.246	0.233	0.084	0.207

All GMM-System regressions include sector level control variables, State and time fixed effects. Up to the fifth lag of the endogenous variables were used as instruments for the endogenous variables. Robust standard errors, clustered at the state-year level, are reported in parentheses. * 0.1 ** 0.05 *** 0.01.

The coefficients of road investments are greater as expected since the exclusion of state level roads might not capture all the effects of the country's highways network on productivity[14]. The external instruments play an even more important role in those estimations since state level highways are more likely to be endogenous to sector productivity by state. According to the Table 2, all regression[15] present valid instruments.

3.2. Road quality

The next step in our empirical exercise is to consider the quality dimension of highway infrastructure. States present different endowments of federal and state level roads with implied quality heterogeneity. A one kilometer of road in good condition may disproportionately affects productivity compared to a road in bad condition. Some studies have proven this point to several infrastructure sectors, especially applied to Brazil (Medeiros and Ribeiro, 2020; Medeiros, Ribeiro and Amaral, 2021). Whether it occurs, our estimates using only road stocks are inappropriate to represent the Brazilian infrastructure case, and our previous estimates could suffer from a measurement error bias. Table 3 shows results under several specifications to give robustness to our findings.

Table 3. *Highways impact on productivity: road quality*

	Overall, Exogenous	Overall, Endogenous	Overall excluding SP	Paving	Signaling	Geometry
Productivity, lagged	0.146**	0.226***	0.227***	0.227***	0.226***	0.228***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Highways (Stock*Quality) *φ	0.086***	0.124***	0.117***	0.133***	0.146**	0.169***
	(0.01)	(0.03)	(0.03)	(0.04)	(0.06)	(0.06)
Observations	14838	14838	14271	14838	14838	14838
Instruments	49	64	61	64	64	64
R^2 Adjusted						
Arellano-Bond test for AR(2) in first difference (p-value)	0.816	0.366	0.356	0.363	0.364	0.353
Hansen test of joint validity of instruments (p-value)	0.199	0.204	0.220	0.209	0.222	0.213

All GMM-System regressions include sector level control variables, State and time fixed effects. Up to the fifth lag of the endogenous variables were used as instruments for the endogenous variables. Robust standard errors, clustered at the state-year level, are reported in parentheses. SP denotes São Paulo. * 0.1 ** 0.05 *** 0.01.

Like the previous estimations, the exogenous specification of infrastructure seems to generate an underestimation bias. The results are robust to the exclusion of São Paulo as well as to

[14] This comparison is taken with cautious, as the period is different.

[15] We have tested several specifications controlling for endogeneity issues, road quality, regional heterogeneity, and outliers, which were not reported but are available upon request. All these robustness tests maintain our main baseline results

the three measures of road quality in the *CNT* Survey. Using column 2 and taking the sample average of φ equal to 0.048, the sector average output elasticity of highway investment is 0.006. It represents an upward bias of 16% using isolated road stock measure. This result is likely coming from the poor condition of highways in Brazil, especially in those states with higher infrastructure reliance and lower productivity levels[16].

3.3. Highway impacts on productivity: the long and the short of it

Our previous estimates describe the short-run elasticities of road investment (α_1), measuring the immediate (within the year) response of sector productivity to a temporary shock in road investments. Now we turn our analysis to calculate the long-run elasticity, which represents the accumulated shock of an infrastructure investment shock in year t over time (Pesaran and Zhao, 1999). Our GMM-System model embeds temporal dynamics into the model, which allows us to calculate long-run coefficients. More formally, in the steady state we have $Y_{js}^{P} = Y_{jst} = Y_{jst-1}$. Rearranging (5) or (6) we have:

$$Y_{js}^{P} = \alpha_0 + \gamma Y_{js}^{P} + \alpha_1 * \varphi_j * Highways(Stock)_{st} + \beta' * Controls_{jst} + \varepsilon_{jst} \qquad (11)$$

Solving equation (11) for Y_{js}^{P}, we obtain the long-run coefficient of road investment as follow:

$$\alpha_{1_{long-run}} = \frac{\alpha_1 * \varphi}{1-\gamma} \qquad (12)$$

$\alpha_{1_{long-run}}$ gives the usual *ceteris paribus* interpretation[17]. Figure 1 shows the short and long-run elasticities under our several previous specifications. All estimated long-run elasticities are significant at 1% level.[18]

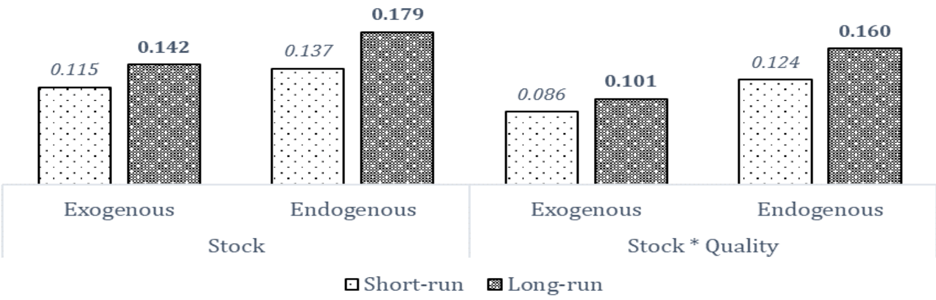

Figure 1. *The short and long-run impact of transportation infrastructure ($\alpha_{1long-run}$) on productivity*

Notes: Exogenous refers to infrastructure treated as an exogenous variable; Endogenous refers to infrastructure treated as an endogenous variable using all the preferred instruments. Short-run is the value for the short-run coefficient; Long-run is the value for the long-run coefficient.

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[16] Since our quality measure is based on arbitrary weights applied to each road quality grade (Equation (4)), we have tried several other weightings to give robustness to our results. Those estimates are also available upon request.

[17] We can test (12) by applying z-test statistics to nonlinear combinations of estimated parameters under the null hypothesis that the long-run elasticity is zero.

[18] The regressions results are available upon request.

In our preferred endogenous specification including both road stock and quality, $\alpha_{1_{long-run}}$ is 0.160. This increasing[19] of 29% compared to the short-run elasticity of 0.124 may be related to the temporal complexity of infrastructure investment, which demands a long time to mature and be effectively offered to firms and individuals. Adjusting to new highways can take a long time. Also, the productivity effects of reducing travel times, traffic accidents and emissions may not be captured in the short term.

Next, we calculate the long-run elasticities considering the sectors infrastructure reliance[20]. We test the values of φ at the percentiles 10, 25, 50, 75 and 90, which are all statistically significant[21]. Figure 2 illustrate the way of how road investment affects productivity by infrastructure reliance level.

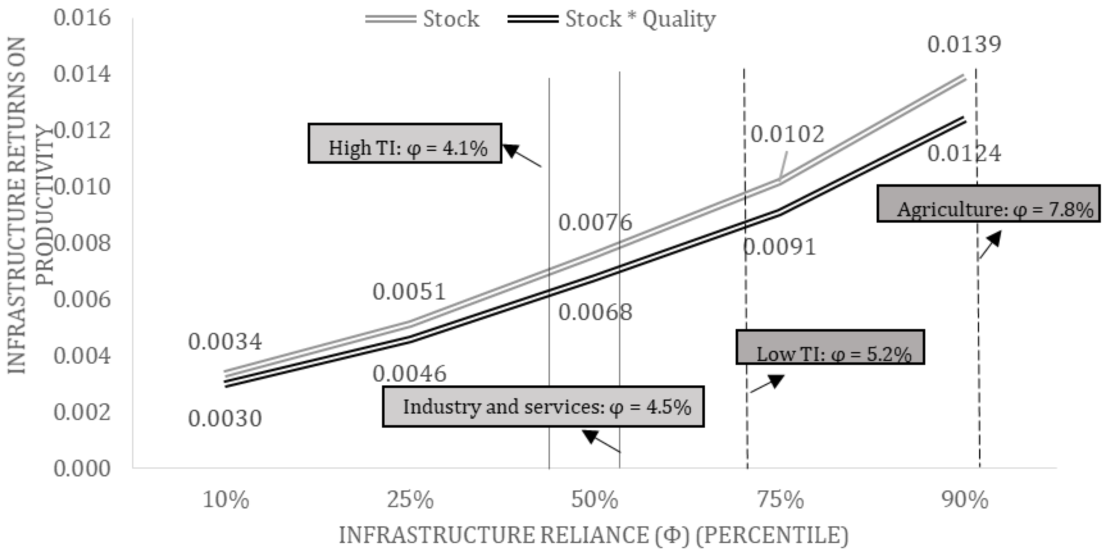

Figure 2. *Highways impact on productivity under different levels of infrastructure reliance (φ)*

Note: TI refers to technological intensity. High TI aggregates medium, medium-high and high TI sectors; Low TI aggregates medium-low and low TI sectors.

We have also tested the long-run elasticities taking the values of φ by each sectoral stratification using our preferred specification with infrastructure as an endogenous variable. Agriculture sector and low R&D technological intensity (including both low and medium-low TI sectors) are the most benefited from road investment increasing, while the high R&D technological intensity (including high, medium-high, and medium TI sectors) and manufacturing and services sector gain less from road improvements in Brazil. This finding is relevant and provide new evidence on the heterogenous infrastructure impacts from the sectoral point of view.

[19] This increasing varies from exogenous/endogenous and stock/stock and quality specifications.
[20] The same set of nonlinear combinations tests are performed, although including the values of φ.
[21] All regression results are available upon request.

3.4. Rate of return to highways investments in Brazil

Having found the values of the short and long-term elasticities considering highway stock and quality, we are able to calculate the economic rate of return to highways investment in Brazil described in equations (1) and (2). To calculate (2), we need information on the state-level GDP-road stock ratio. The state GDP is available from the IBGE. However, our road measure is physical and there is no monetary estimation of road stocks from official sources. To overcome this issue, we follow Li et al. (2017) and use an external source based on the standard perpetual inventory method. Frischtak and Mourão (2017) calculated the sectorial infrastructure stock in Brazil between 1970 and 2016, period that covers our study. They found the stock of transportation infrastructure to be around BR R$ 743 billion in 2015, of which BR R$ 371,5 billion (50%) were in the road sector. The Brazilian GDP was almost BR R$ 6 trillion, suggesting a GDP-road stock ratio of 16, almost double the Chinese ratio used by Li et al. (2017). It shows the precarious condition of road infrastructure in Brazil.

From Frischtak and Mourão (2017), we can calculate the value of each kilometer of road by dividing the value of national road stock by the length of roads. It gives us the value of BR R$ 1,91 million per road as the road length was 194,243 km in 2015. Then, we can multiply the value per km of road by the road length of each state. However, following this approach would lead us to a critical measurement error. We would assume that a high-quality km of road has the equal value of a poor-quality km of road, which is not valid in the literature (Medeiros and Ribeiro, 2020; Medeiros, Ribeiro and Amaral, 2021; Wang, Wu and Feng, 2020). Then, we obtain the value per km of road using our measure of infrastructure in Equation (9) that accounts for both stock and quality. In this way, we can distinguish the road quality heterogeneity of each state and consistently evaluate the economic rate of return to highway investments.

Another issue in applying Equations (1) and (2) is that we have not the value-added weight by sector by state. This weight is important as states has different sector specializations. Then, we proxy ω_{js} as the wage share by sector by state. We need to be cautious with our results as the wages and value-added weights may differ by sectors as well. To give robustness to our findings, we also generate a return rate taking the national average ξ by multiplying α_1 by the average φ, instead of varying ξ by state.

Table 4 summarizes our calculated return rates to highways investments in Brazil. As expected, using the measure based only in the road length generates an upward biased rate of return. It is coming from the GDP-road stock ratio (Y/G) that is greater in the stock measure in relation to the stock weighted by quality measure, since it assumes that the roads have the same monetary value in the country. By correcting our road investment measure by including road quality heterogeneity, we have obtained a more reliable rate of return to highway investment of 17.2% in the short-run and 22.1% in the long-run taking the average of National ξ and State varying ξ. This rate of return indicates the high rentability of road investments in Brazil and are in line with the rate of return of 25.9% in China found by Wang, Wu and Feng (2020). They are also in line with Li and Chen (2013) and Li *et al*. (2017) using different approaches.

Table 4. *Return rate to highways infrastructure investments.*

Measure/coefficient	National ξ		State ξ	
	Short run	Long run	Short run	Long run
Highways (stock)	22.54%	24.91%	22.14%	28.92%
Highways (stock * quality)	17.26%	22.26%	17.17%	21.93%

Notes: National ξ is calculated using φ equal to the national average 0,048; State average ξ is the weight the sector wages in the total weight by sector and multiply it by φ_s. Short-run uses the values for the short-run coefficients (Figure 3); Long-run uses the values for the long-run coefficients (Figure 1).

We cannot directly compare our result with Wang, Wu and Feng (2020), since they used firm-level data. However, we have some arguments to explain our smaller rate of return compared to the Chinese one. First, the Brazilian transport of cargo and passengers is highly concentrated in the road sector. This mode exhibits higher freights values compared to other modes as railways and waterways, and its current poor quality strangle the highway network. In this sense, it is likely that investments in roads in highly road dependent states and countries are less effective compared to investments in other modes of transport. In addition, Wang, Wu and Feng (2020) considered the investments in the transport sector as a whole, which may be which may have captured a greater infrastructure impact. Second, the changes in both infrastructure investments and productivity growth, although substantial during a considerable part of the PAC period, are not comparable to the Chinese scenario, which may help to explain the rate of return differences. Lastly, in Brazil productivity grown more in sectors with lower levels of productivity, probably influencing the rate of return value.

To evaluate the magnitude of our rate of return to highway investment, we can compare it with the Social Discount Rate (*TSD*) of 8.5% used by the Ministry of Economy (2021) in evaluating infrastructure projects. To reduce our rate of return of 22.1% to the threshold of 8.5%, Brazil would need 2.6 times more highways, which implies a road stock (weighted by its quality) of around 16% of the national GDP. This finding corroborates the estimates by Frischtak and Mourão (2017) predicting an ideal road stock of 13.5% of the GDP. Considering long-run real rates of return from 4% to 5% worldwide, Brazil would need to improve its road stock by 4.4 times, reinforcing the high rentability of highway investments in the country in our sample period.

4. Concluding remarks

We find that road investment had a substantial positive effect on Brazilian sector-level productivity between 2007 and 2017. We overcome endogeneity issues between infrastructure and productivity by proposing a novel econometric approach including both internal and external instruments. Also, by using a dynamic model with past value of the dependent variable, we can calculate short and long-run elasticities of road investments. We correct measurement errors coming from road measures by including a novel road quality indicator. Our findings show a sector average productivity elasticity of highway investment of 0,006, which is in line with previous studies. These results remain under several specifications controlling for endogeneity issues, road quality, regional heterogeneity, and outliers. We identify relevant biases coming from endogeneity and road errors measurement issues. We also find an increasing of 29% in the productivity elasticity of infrastructure in the long-run compared to the short-run, proving the broad discussed long-run characteristic of infrastructure investment. By our preferred model, we calculate a return rate to road investments equal to 22.1%, proving its efficiency in Brazil.

While we contribute to the literature in umpteen ways, there are several issues worth further discussion. First, while our sample cover a broad number of heterogenous sectors, it may not fully capture the dynamic of some of them. As RAIS is a formal labor dataset, it may bias the productivity count of highly informal sectors as agriculture and construction. Further research on this sector is needed. In addition, our results are based on a sample that maintains an economic structure over time. In other words, we are assuming that sector infrastructure reliance does not change. However, infrastructure may promote structural transformation (Redding and Turner, 2015), and the infrastructure impacts on productivity might be confounded with a reallocation effect across sectors. Better understanding those mixed effects is also important. Lastly, as we calculate a return rate based on sector-level productivity measure, we may not fully capture the social rate of return of road investment. For instance, benefits in terms of poverty and pollution alleviation are expected from road improvements, which may be computed in future research.

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