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The Impact of Transport Infrastructure on Productivity in Canada

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Abstract

This study examines the relationship between transportation infrastructure and output and productivity in Canada. We estimate different specifications of a static Cobb-Douglas production function (in levels and in differences). The impact of highway infrastructure is mixed. For the 1997-2018 period a higher stock of highways does not translate into higher productivity for the business sector, But from 2009 to 2018, the impact of highways is positive and statistically significant, when we account for province-specific characteristics. The long run elasticity of output with respect to railway lines is statistically significant and quite large (0.27). For this type of infrastructure, then, our results are more conclusive and point to a positive impact of railways on output and productivity.

The Impact of Transport Infrastructure on Productivity in Canada

Executive Summary

In 2016, the government of Canada announced that, as part of its Investing in Canada plan, it would invest $10.1 billion over the next decade in trade and transportation infrastructure projects. Investment in the transportation network is commonly seen as a way to boost productivity growth, support job creation and, in turn, increase economic growth. Indeed, the literature suggests that transportation infrastructure improvements can facilitate trade and increase regional specialization which in turn can lead to productivity gains. The objective of this report is to estimate the impact of transport infrastructure on productivity in Canada.

This study examines the relationship between transportation infrastructure and output and productivity. We estimate different specifications of a static Cobb-Douglas production function (in levels and in differences). Suspecting that investment in infrastructure could affect output with a lag, and to control for the possible non-stationarity in output time series, we also estimate a dynamic production function that includes lags of the dependent variable and our variables of interest. We do so with OLS and System GMM. In order to further explore the relationship between transportation infrastructure and productivity, we also estimate a multifactor productivity growth function. Finally, since the original dataset did not allow to disaggregate transportation infrastructure sufficiently, we also estimate the static functions using an alternative data set that allows a more granular disaggregation but covers a shorter time period. This allowed us to estimate the impact of railway lines, seaports and airports.

Looking at the impact of highways first, we find that for the period spanning from 1997 to 2018 (i.e. the original dataset), a higher stock of highways does not translate into higher production for the business sector, both when we account and do not account for province-specific effects. However, when using the alternative dataset, which ranges from 2009 to 2018, it appears that the impact is positive and statistically significant, but only when we account for province-specific characteristics. It is possible that the time period used in our estimation could have an impact on the coefficient estimates, which is why our results differ from one dataset to the other.

Using the coefficient estimates from the dynamic production function, we also find that the long run elasticity of highways is positive (0.07 to 0.10), which is consistent with the literature Overall, our results on road infrastructure are not very conclusive, which is more in line with the more recent literature, as opposed to the earlier findings of Aschauer and others.

We then look at the impact of railways. In the first dataset, the coefficient estimates on other transportation infrastructure (which includes railway lines) align with the coefficient estimates on railway lines from the alternative dataset which is reassuring and confirms that other transportation infrastructure was a good proxy for railway lines. The coefficient estimates remain positive across most specifications in the business sector. Moreover, the long run elasticity of output with respect to railway lines is statistically significant and quite large (0.27). For this type of infrastructure, then, our results are more conclusive and point to a positive impact of railways on output and productivity.

For the stock of marine engineering infrastructure, coefficient estimates are mostly non-statistically significant and oscillate between small positive and negative values.

In our industry-specific analysis, we find a positive and robust impact of railway lines on production in the transportation and warehousing sector. Using the original dataset, the coefficient estimates are positive and statistically significant across specifications. The relationship also appears robust to the use of the alternative dataset. Moreover, the long run elasticity of output with respect to railway lines in the transportation sector is quite large (0.10 to 0.17). Road infrastructure also appears to have a positive impact on production when we do not account for province-specific characteristics. It is not surprising that the transportation and warehousing sector would benefit from improvements in those two categories of transport infrastructure.

In the manufacturing sector, road infrastructure appears to have a positive impact on production (based on most specifications) while marine engineering construction would translate into lower production. This suggests a positive association between additional stock of highways and roads and production in the manufacturing sector but the opposite association with the stock of marine construction.

While our results are sometimes contradictory between specifications, or often not statistically significant, this analysis sheds some light on infrastructure needs at the aggregate business level as well as at the sector-specific level in Canada. It does so using two different datasets over two different time periods. Our results are most conclusive regarding railway infrastructure, and indicate that the association between transport infrastructure and output can vary widely between sectors. Further research could potentially shed some light on some of the incongruities we found. For example, we could estimate a translog production function, or take a cost function approach which would allow to verify some of the results we obtained here. This would also give us a better understanding.

The Impact of Transport Infrastructure on Productivity in Canada*

1 INTRODUCTION

In 2016, the government of Canada announced that, as part of its *Investing in Canada* plan, it would invest $10.1 billion over the next decade in trade and transportation infrastructure projects. Investment in the transportation network is commonly seen as a way to boost productivity growth, support job creation and, in turn, increase economic growth.

Indeed, the literature suggests that transportation infrastructure improvements can facilitate trade and increase regional specialization which in turn can lead to efficiency gains. More specifically, a more efficient transportation network lowers travel costs. Firms will have access to a larger market and will be able to lower their inventory levels as just-in-time delivery becomes possible. In turn, production costs will decrease, and firms will reap the productivity gains. Moreover, as better transportation facilitates spatial agglomeration, firms will take advantage of the proximity of other firms in order to innovate and will adopt or develop more productive production processes.

This argument holds for all transport infrastructure, but looking at rail infrastructure in particular, we note that improvements there allow travel over longer distances, and a larger market expansion. Rail infrastructure also has the potential to reduce transport costs since rail transportation is a cheaper alternative to trucking in some cases. Lower costs can in turn lead to higher productivity. In some specific cases, rail infrastructure has also the potential to reduce road congestion and reduce costs related to road construction and maintenance.

Marine infrastructure such as ports also plays an important role in trade development. Ports allow for greater access to international markets. Investment in port infrastructure will likely result in greater reliability, reduced damages and better ability to track shipments which would all contribute to logistics performance. This will in turn increase market access which could improve labour supply, production, innovation, competitiveness and economic restructuring, all contributing factors of productivity growth (Lakshmanan, 2011).

Another channel through which transportation infrastructure investment can stimulate efficiency is through competitiveness. In order to remain competitive amid market expansion, firms are forced to lower prices, increase quality and innovate, with only the most efficient firms remaining on the market. Market expansion, enabled by better transportation infrastructure, also increases the range of skills available to firms, which can lead to improved labour quality and lower costs. In the same way, land and other factors of production become more abundant as transportation costs decrease (Lakshmanan, 2011).

Many authors (Aschauer, 1989; Khanam, 1990; Canning and Fay, 1993; Fernald,1999; Berechman, Ozmen and Ozbay, 2006; Jiwattanakulpaisan *et al*., 2012) have tested this theory using econometric tools and have found evidence that transportation infrastructure stock has a positive impact on productivity. However, these results have been the subject of many criticisms. Some authors have indeed discredited this positive relationship (Hulten and Schwab, 1991; Evans and Karras, 1994), pointing to different model misspecifications.

This report examines the question using recent data from Canadian provinces over the 1997-2018 period. It uses data on public and private transportation infrastructure broken down bycategory, to distinguish between the potential effects of roads, railways, seaports, and airports. The use of panel data also opens the door to a multitude of econometric methods, allowing us to provide a number of robustness tests for our results. Moreover, our data being disaggregated to the industry level, we provide results for several industries separately in addition to the whole business sector.

* This report was written by Paskynel Jacques-Arvisais, an economist at Transport Canada, and Simon Lapointe, an economist at the Centre for the Study of Living Standards (CSLS) at the time of the writing.The CSLS thanks Transport Canada for financial support.

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More specifically, we estimate different specifications of the Cobb-Douglas production function, both in levels andin differences in order to address different criticisms from previous analyses. We account for autocorrelation, contemporaneous cross-panel correlation, as well as heteroskedasticity. We also estimate the impact of transportation infrastructure on multifactor productivity.

Finally, we explore adynamic production function, by including lags of the dependent and independent variable, to estimate the long-term relationship between transportation infrastructure and productivity.

As mentioned earlier, we disaggregate transportation infrastructure into different components: highways, roads, bridges, and overpasses; other transportation infrastructure (which includes, amongst others, railway lines); and marine engineering construction (which includes, amongst others, seaports and canals).

Our main results are as follows. Our analysis shows that other transportation infrastructure, with railways representing 32% of this category in 2018 (the remaining 68% accounting for parking lots, runways, and other), has a positive impact on the GDP of the business sector. This result remains somewhat consistent across model specifications, both for static and dynamic production functions. We also confirm the positive impact of railways by using an alternative dataset which allows us to isolate railway lines, although only covering a shorter period of time. Firms could thus benefit from improvements in railways infrastructure.

Road infrastructure, which includes highways, roads, streets, bridges and overpasses, appears to havea negative and statistically significant impact on GDP. However, using an alternative dataset, we find that the stock of highways is positively associated with production when we account for provincial fixed effects. This alternative dataset thus suggests that firms could benefit from an increased stock of highways and other road infrastructure. However, given the smaller sample size of this alternative dataset and the shorter time period covered, uncertainty remains whether roadinfrastructure has an impact on output.

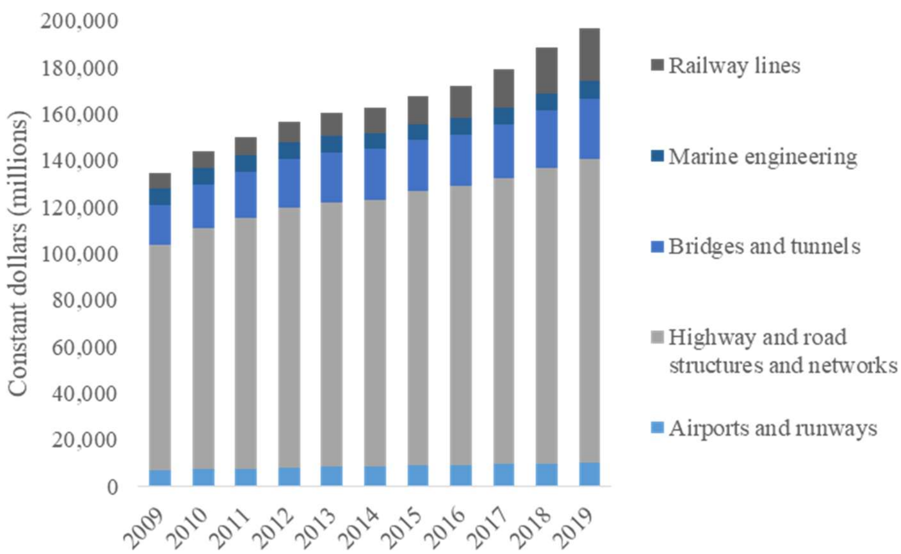
We do not find any strong evidence supporting the need for additional marine engineering infrastructure.

Section 2 presents some general trends on transportation infrastructure and productivity in Canada. Section 3 reviews findings and methodology from previous studies as well as model misspecifications which we later integrate into our econometric analysis. The fourth section presents the theoretical framework. The fifth section discusses the methodsused for our econometric analysis, while the sixth section presents the data used in the estimation. Section 7 presentsour results and discuss implications. Section 8 concludes, presenting overall results as well as potential future research areas.

2 CONTEXT

In 2019, the stock of transportation capital, net of depreciation, amounted to $196,907 million in constant price terms (2012 dollars), or 46.3% more than a decade ago. This total includes airports, bridges, highways and roads, ports, railway lines, runways, tunnels, and marine infrastructure.

Figure 1: Infrastructure Economic Accounts, net stock by asset



The stock of transportation infrastructure per worker increased from $8,044 in 2009 to $10,333 in 2019in constant terms. The share of investment in transportation infrastructure to gross domestic product increased slightly from 1.2% in 2009 to 1.3% in 2018.

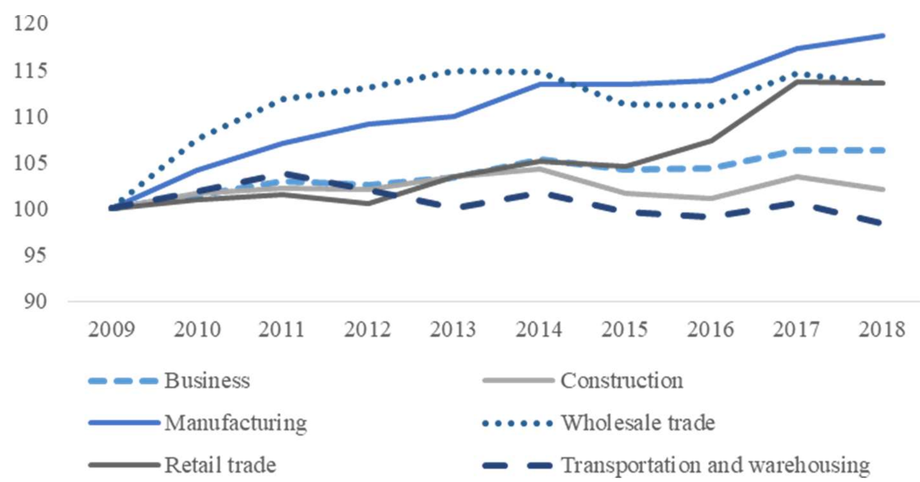
This increased investment in infrastructure is reflected in data on the remaining useful life of assets. More specifically, we measure this with the difference between the average age of assets and their expected service life. The remaining useful service life of Canadian infrastructure has increased from 53.4% to 56.0% between 2009 and 2019. In other words, a larger share of their useful economic life remains today than it did 10 years ago. For highways specifically, this share increased from 56.8% to 59.1%.

There are large disparities across provinces, with the largest share of remaining useful service life of highways found in Alberta and the lowest in Prince Edward Island. The share of remaining economic life for railway lines increased from 51.8% to 58.1%, with the highest share in Ontario and Quebec, at approximately 64% in both provinces, and the lowest in Prince Edward Island, at 32.8%. Marine engineering construction's share remained unchanged at approximately 40.0%, with the highest sharein Quebec, at 47.8%.

As depicted by the large differences in remaining useful service life rates, investment needs in transportation infrastructure vary greatly between provinces and infrastructure categories.

Despite the large increase in the stock of transportation infrastructure over the last decade, multifactor productivity does not seem to have increase significantly. Multifactor productivity increased by an average of 0.7% annually between 2009 and 2018 in the business sector as a whole. In the transportation and manufacturing sector, it declined by 0.2% annually on average over the same period. On a more positive note, it increased by 1.9% on average in the manufacturing sector.

Figure 2: Multifactor productivity index, by keysector



3 LITERATURE REVIEW

It was Meade (1952) who first treated public capital as an unpaid factor of production, contributing to the production of private entities. Later, Ratner (1983) and Eberts (1986) incorporated public capital to the production function. However, it wasn't until Aschauer (1989) measured the output elasticity of public capital that it became a subject of debate. Aschauer (1989) hypothesized that the decline in public infrastructure investment in the 1970s and 1980s in the United States could be the cause of the productivity slowdown observed during the same period. He suggested that public capital investment could increase the productivity of private capital which in turn could lead to more investment in private capital.

Aschauer (1989) added public capital stock as an input in an aggregate Cobb-Douglas production function and produced estimates of output elasticity that were considerably higher than private capital's output elasticity estimates. This raised many questions concerning the role of public capital s tock on the private sector's production but also about the validity of the estimates. Aschauer (1989) found that a 1% increase in the ratio of public to private capital stocks increased capital productivity by 0.39% whereas the ratio of labor to private capital increased capital productivity by only 0.35%.

Many have tried to replicate and to refine the techniques used by Aschauer in order to validate orinvalidate the output elasticity estimates of public capital. Cost and production functions have been used to measure the role played by public capital in the private sector's production. Munnell (1990) found a similar relationship although to a smaller degree than in Aschauer (1989). Munnell (1990) also estimated a translog production function in order to study the relationshipsbetween public capital and private inputs. She used aggregate public capital as well as disaggregated public capital in order to better understand those relationships. She found that aggregate public capital was a substitute toprivate capital, and more specifically, that highways and streets were substitutes to private capital, water and sewer facilities were complements to private capital while other infrastructure such as schools and hospitals appeared to be substitutes to private capital.

Canadian studies have also been conducted. Khanam (1990) used both time series data for the goods-producing sector as well as yearly data disaggregated at the provincial level to estimate the Cobb- Douglas and translog production functions to estimate the output elasticity of highway capital. She found that the output elasticity of highway capital ranged from 0.09 to 0.17.

Canning and Fay (1993) estimate a Cobb-Douglas production function using a panel of 96 countries of the 1960-1985 period. The authors use an aggregate of kilometers of paved roads and railway lines asa measure of transportation infrastructure. They conclude that transportation infrastructure should be considered as a condition for economic growth opposed to a factor of production.

Evans and Karras (1994) estimate both a Cobb-Douglas and a translog production functions using panel data for the48 U.S. states over the 1970-1986 period. They address different issues of misspecification by estimating their regressions in difference, correcting for serial correlation and endogeneity as well as disaggregating public capital and services in different components. They find robust evidence that government educational services has positive productivity while government capital has negative productivity. They conclude however that this doesn't mean thatgovernment capital is over supplied but rather that it may be mispriced.

Wylie (1995) used time series data for goods-producing industries and estimated a Cobb-Douglasproduction function as well as a translog production function. The estimated output elasticity of public infrastructure ranged from 0.248 to 0.517. The functions are estimated in log-level and the DurbinWatson statistic is smaller than the R2 which could indicate the presence of spurious regression.

Fernald (1999) explores how roads contribute to the productivity of industries in the U.S. over the 1953-1989 period. The author hypothesizes that industries using road transportation more than average, should also benefit from roads more than average. After estimating a production function, the author concludes that roads are not productive at the margin, despite the fact that they were very productive before the 1970s.

Berechman, Ozmen and Ozbay (2006) estimate a production function using state-, county- and municipality-level data. They find that highway capital has a positive impact on output at the state and county level. They also estimate a lag model and a spillover model in order to better understand the large disparities of estimates in the literature. They find that when lags are introduced, the output elasticities with respect to transportation infrastructure tend to decrease. They also find that spillover effects from transportation infrastructure can be observed when using municipality level data, withestimates decreasing as the geographical scale decreases.

Jiwattanakulpaisan et al. (2012) examine the productivity performance of additional highway capacity in the U.S. The authors use a physical measure of highway infrastructure, i.e. lane-mile. They estimate a dynamic Cobb-Douglas production function and find that expanding highway infrastructure increases private sector output within and outside states. However, the benefits are found to be small.

There have been many debates over the validity of the estimates found by Aschauer and subsequently by others, likeMunnell. Tatom (1991) argued that the relationship between public capital and the private sector's output is spurious. He argued that estimating the production function in level could result in the estimation ofa spurious relation between public capital and output production, which both trend upward. Aaron (1990) also claimed that the estimates found by Aschauerand Munnell were improbably high and thus, could not represent the real effect of public capital on production. Others pointed to the fact that elasticity estimates have varied greatly throughout the literature which demonstrates the fragility ofthe relationship between the two. Reverse causation has also been pointed as a potential source of bias which would leadto the overestimation of the impact of public capital stock on production. Others have raised the difficulty of measuring public capital stock as a potential threats to the consistency of OLS estimators. Finally, criticism against missing variables has been raised, which could also produce unreliable estimates.

Melo, Graham and Brage-Ardao (2013) conducted a meta-analysis on the impact of transport infrastructure on output in order to provide insights on model specifications and estimation methods. The authors point to two major issues which have characterized early estimates of the impact of transport investment on the economy, namely, simultaneity bias and omitted variable bias. As a result,the estimates produced would be inconsistent. The studies included in the meta-analysis used a production function in order to estimate the output elasticities of transport infrastructure. Studies that omit to correct for the omitted variable bias and unobserved heterogeneity or control for urbanization level, congestion and spatial spillover effects tend to produce biased estimates. They also found that studies using instrumental variables to control for reverse causality produced higher estimates. The size of output elasticity estimates also vary depending on the chosen economic sector, transport mode, measure of infrastructure, country and time frame. The choice of econometric estimator can also influence the size of the estimates.

The authors hypothesize that the level of regional aggregation can also affect the size of the estimates as investment could either increase national output or relocate production to another area. The industrial scope chosen is also assumed to influence the size of the estimates as some industries, more reliant on transportation services, might lead to higher output elasticities. By scoping the literature, they find that the manufacturing sector has larger (but more dispersed) average estimates than the overall economy while services and construction sectors produce smaller output elasticities on average. The mode of transport appears to also influence the size of the estimates with roads having the largest impact on output and airports, the smallest.

The time period used could also potentially affect the size of the estimates since marginal benefits from transportation infrastructure investment will tend to decline as the network develops (diminishing returns). The size of the estimates differs slightly betweenshort-runandlong-runoutput elasticity (which depends on the econometric estimator used, panel vs time series data, static vs dynamic models),where long-run estimates tend to be larger. The choice of measurement of infrastructure (monetary or physical values) appears to affect the size of the estimates, with monetary value leading so smaller estimates.

The results from the estimation of the meta-regression models support the hypothesis of the authors regarding the use of panel data estimators. Fixed-effects and GMM estimators seem to produce smaller estimates than OLS estimators. They also find that controlling for urbanization as well as for both urbanization and spatial spillovers lead to lower estimates whereas controlling for congestion leads to higher estimates.

4 THEORETICAL FRAMEWORK

We start by exploring the production function framework. Assume that the production function takes the following form:

$$Q = A(T) * F(K, L, T)$$

In that equation, Q is output, K is (non-transportation) capital, L is labour, and T is transportation infrastructure. The term $A(T)$ represents technological progress, and depends on transportation infrastructure T. Assuming a Cobb-Douglas production function, and that $A(T) = A^{*}T^{\eta}$, we can expressthe production function as such:

$$\ln(Q) = \ln(A^{*}) + (\eta + e^{T})\ln(T) + e^{K}\ln(K) + e^{L}\ln(L)$$

Here, e^{j} is the elasticity of output with respect to input j. Some authors choose to set $e^{T} = 0$, thus assuming that transport infrastructure only affects outputs through the Hicks-neutral technical change parameter A (Melo et al., 2013). To estimate this equation, we need assumptions on the returns to scale. With constant returns to scale across capital and labour, then $e^{K} + e^{L} = 1$, and then:

$$\ln(Q) - \ln(L) = \ln(A^{*}) + (\eta + e^{T})\ln(T) + e^{K}[\ln(K) - \ln(L)]$$

In Aschauer (1989), the author assumes constant returns to scale across all factors, obtaining

$$\ln(Q) - \ln(L) = \ln(A^*) + (\eta + e^T)[\ln(T) - \ln(L)] + e^K[\ln(K) - \ln(L)]$$

Jiwattanakulpaisarn et al. (2011) and Jiwattanakulpaisarn et al. (2012) use a similar approach, starting from the following production function, where *H* is the physical measure of highway stock and *Urban* avariable indicating the share of the state that is urbanized:

$$Q_{it} = A(H_{it}, Urban_{it}, \mu_i, \tau_t) * F(K_{it}, L_{it})$$

They use a panel of US states covering the 1984-1997 period. They assume that the Hicks-neutral parameter takes the following form:

$$A = H^{\beta H} e^{\beta u_i Urban_{it}} e^{\mu i} e^{\tau t}$$

They also assume that the production function takes a Cobb-Douglas form, and find the following equation to estimate:

$$\ln(Q_{it}) = \alpha + \beta_L \ln(L_{it}) + \beta_K \ln(K_{it}) + \beta_H \ln(H_{it}) + \beta_u Urban_{it} + \mu_i + \tau_t + \varepsilon_{it}$$

In contrast to the previous equation used in Aschauer (1989) and La Ferrara and Marcellino (2000), they do not assume constant returns to scale in labour and capital (i.e., that $\beta_L + \beta_K = 1$). The model also explicitly contains state (μ_i) and time (τ_t) fixed effects. Jiwattanakulpaisarn et al. (2011) then augment that model with dynamic parameters, assuming that the error term follows an auto-regressive pattern of degree 1 (i.e., an AR(1) model).

Transport infrastructure could have different impacts depending on the industry. For example, the manufacturing industry may benefit more from better transportation: firms receive their intermediate outputs on time or can trade with other countries. On the other hand, service industries may depend less on the quality of roads and airports. In addition, the fact that impacts vary by industry mean that even if for the overall economy, the analysis finds that transportation infrastructure has no impact, it may hide industry-specific effects. To test these ideas, we perform the analysis using GDP and inputs (hours worked and private capital) for specific industries. However, since transportation capital stock is most likely not industry-specific (e.g. built and owned by the public sector), this input will be the same in every industry-specific analysis.

5 ECONOMETRIC SPECIFICATION

The analysis is separated in four main sets of estimates: static estimations using output levels, differenced estimations using output levels, differenced estimations using MFP, and dynamic estimations using output levels and lags of the output level as independent variables.

We start by estimating the following regression using the level of output, based on the work of Jiwattanakulpaisarn et al. (2011) and Jiwattanakulpaisarn et al. (2012):

$$\ln(Q_{it}) = \alpha + \beta_L \ln(L_{it}) + \beta_K \ln(K_{it}) + \beta_H \ln(H_{it}) + \beta_R \ln(R_{it}) + \beta_M \ln(M_{it}) + \beta_u \ln(Unemployment_{it}) + \mu_i + t + \varepsilon_{it}$$

This equation estimates the elasticity of output with respect to different categories of transportation infrastructure. Specifically, *Q* represents real gross domestic product, *L* hours worked, *K* non-residential capital (other than transportation), *H* highway, roads and bridges, *R* other transportation infrastructure (which includes railway lines), *M* marine engineeringinfrastructure.

The equation also includes a time trend,[1] and, in some specifications, we also include provincial fixed effects (μ_i). We also control for the unemployment rate which captures current economic conditions, as suggested by Melo *et al.* (2013).

The equation is estimated on a panel of provinces indexed by *i* over the 1997-2008 period (for the main analysis) with years indexed by *t*, using total business sector output as the dependent variable. Secondary estimations are also estimated using industry-specific output as the dependent variable, and industry-specific non-transportation capital and hours worked as independent variables.

We then estimate the same model in differenced form:

$$\Delta\ln(Q_{it}) = \alpha + \beta_L\Delta\ln(L_{it}) + \beta_K\Delta\ln(K_{it}) + \beta_H\,\Delta\ln(H_{it}) + \beta_R\Delta\ln(R_{it}) + \beta_M\,\Delta\ln(M_{it}) + \beta_U\Delta\ln(Unemployment_{it}) + \varepsilon_{it}$$

This equation estimates the impact on output growth due to growth in the inputs, including the stock of transportation infrastructure. This model offers another way to control for fixed effects by differencing them away, and might provide better estimates if the errors in the first equation are auto-correlated (i.e.the data are non-stationary).

To estimate the impact of transportation infrastructure on multifactor productivity, we estimate the following equation based on La Ferrara and Marcellino (2000) and Aschauer (1989):

$$\Delta A_{it} = \alpha + \beta_H\,\Delta H_{it} + \beta_R\Delta R_{it} + \beta_M\Delta M_{it} + \beta_K\Delta K_{it} + \beta_L\Delta L_{it} + \beta_U\Delta Unemployment_{it} + \varepsilon_{it}$$

Where ΔA_{it} is multifactor productivity growth measured as the residual in the usual growth regression ($\Delta A_{it} = \Delta Q_{it} - s^L\Delta L_{it} - s^K\Delta K_{it}$). The residual in the regression equation proposed here captures "true"technological progress (i.e., without the impact of transport infrastructure).

Finally, we estimate models that take into account the dynamic nature of the problem more directly, by including lags of the dependent variable in the equation, as well as lags of the independent variable. Indoing so, we might gather more information on the longer-run effect of transportation infrastructure.

By estimating a dynamic production function, we can also take into account the simultaneity between output and transportation infrastructure. The static Cobb-Douglas production function does not account for the dynamic adjustmentsbetween transportation infrastructure and output. As in Jiwattanakulpaisarn *et al.* (2011), we estimate pooled OLS,fixed effects and system GMM dynamic models.

When including lags of the dependent variable in the equation, pooled OLS and fixed effects dynamic panel models are prone to biases. They are also most likely inconsistent. Therefore, as in Jiwattanakulpaisarn *et al.* (2011), we also turn to a System GMM model. In the System GMM model, we treat all variables as endogenous except for the unemployment rate, which we assumed to be exogenous.[2] We estimate three different System GMM models, for each category of transportationinfrastructure, in order to manage the number of instruments.

[1] We estimated the production function with both a time trend and time fixed effects but do not find the coefficient estimates on the different variables to vary greatly from one specification to the other. For that reason, we only reportresults when the time trend is included. Year fixed effects control for unobserved variables constant across provinces but evolving through time, while the time trend captures technical changes as well as de-trends the data.

[2] Due to the relatively low sample size, we want to limit the number of potential instruments as much as possible

Unfortunately, System GMM assumes that there is no correlation across units of observation (i.e. provinces) in the error term, which is most likely present in our case as we mentioned previously. Moreover, this model works best when the time dimension (T) is relatively small compared to the number of units of observation (N). In our case, the time dimension is larger than the number of provinces.

6 DATA

We construct a panel dataset using data from several sources. This panel covers all provinces over the1997-2018 period for the business sector as well as specific sectors. In our analysis, we focus on the following sectors: manufacturing, transportation, wholesale and retail trade, and construction.

The first consideration is obtaining data on transportation infrastructure. Melo *et al.* (2013) discuss the choice of the transport infrastructure variable. In most studies, a monetary measure is adopted: the value of the transport capital. Other studies measure transport infrastructure using physical values, such as kilometers of road. The advantage of monetary measures is that they are easier to collect on a wide range of transportation infrastructures. However, two investments with the same value, such as an airport and a regional road, might have different impacts on productivity. That being said,to cover a wide range of possible transport infrastructures, this paper uses monetary measures.

Therefore, the stock of private and transportation capital was obtained through a custom request made to Statistics Canada for an extract from the Stock and consumption of fixed capital program. From that request, we obtain the stock of capital in constant dollars for the following asset categories: highways, roads, bridges, and overpasses; other transportation construction; and marine engineering construction. Other transportation construction includes railway lines, parking lots, runways and other. Marine engineering construction includes seaports, marinas and canals. Total non-residential capital stock is also derived from this dataset.

We also obtain data on transportation capital using an alternative dataset which spans from 2009 to 2018: The Infrastructure Economic Accounts, also maintained by Statistics Canada. This data allows a disaggregation of transportation capital in more precise categories. In particular, we can obtain data on railway lines directly instead of including it in "other transportation infrastructure," allowing us to confirm whether the impact of railway lines is well captured by other transportation infrastructure in the original dataset. It also provides us with an additional category of infrastructure: airports.

From both datasets, we include both private and public stock of transportation infrastructure, as the share owned by the private sector is considerable for some transportation assets. Indeed, the private sector contributed to 69% of the stock of airports, 65% of railway lines and 47% of marine engineering construction (such as ports). In addition to data on transport infrastructure, we need additional economic data relevant to the production function. From the Canadian Productivity Accounts maintained by Statistics Canada, we obtain annual data on hours worked, gross domestic product (in chained 2012 dollars), and multifactor productivity. We obtain these data by province and industry . We obtain the annual unemployment rate by province from the Labour Force Survey.

7 RESULTS AND INTERPRETATION

7.1 Static production function in levels

We start by estimating a pooled OLS model with Driscoll-Kraay standard errors for the overall business sector. This model corrects for heteroscedastic, autocorrelated, and cross-sectionally dependent errors. The use of this estimation method is driven by results of tests that show the presence of autocorrelation, cross-sectional dependence and heteroskedasticity in the errors. Results from this estimation are in Column 1 of Table 1.

Table 1: Results using the Static Production Function Model in levels, with ln(GDP) as Dependent Variable

	Pooled OLS	Fixed Effects	FGLS	Prais Winsten	Prais Winsten with fixed effects
Non-transp. K	0.386***	-0.00155	0.352***	0.354***	0.0587
	(14.34)	(-0.04)	(23.09)	(9.99)	(1.01)
Hours worked	0.746***	0.981***	0.625***	0.650***	0.609***
	(43.39)	(9.84)	(23.06)	(10.95)	(5.23)
Roads	-0.201***	-0.0818*	-0.0478***	-0.0637*	-0.0855*
	(-10.53)	(-2.15)	(-3.31)	(-2.13)	(-2.35)
Other (inc. rail)	0.101***	-0.00282	0.0529***	0.0467**	0.0398
	(14.20)	(-0.19)	(7.82)	(2.65)	(1.35)
Marine	-0.0248*	-0.0254	0.0197*	0.0113	-0.0438
	(-2.28)	(-0.98)	(2.21)	(0.45)	(-1.23)
Unemployment	0.155**	-0.00421	-0.0325***	-0.0311	-0.0459**
	(3.76)	(-0.28)	(-4.20)	(-1.96)	(-2.79)
Trend	0.00740***	0.0127***	0.00860***	0.00711***	0.0131***
	(5.85)	(7.94)	(13.99)	(5.05)	(8.16)
Constant	4.487***	5.425***	4.742***	4.716***	11.53***
	(30.82)	(3.97)	(29.11)	(14.79)	(5.65)
N	220	220	220	220	220

Note: Standard errors in parentheses. Independent variables are included in logarithmic form. Columns 1 and 2 report Driscoll-Kraay standard errors estimated using xtscc in Stata. Column 3 report errors corrected for autocorrelation estimated using xtgls in Stata. Column 4 and 5 report errors estimated usingxtpcse in Stata.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

The results indicate a positive impact from other transportation infrastructure (the category that includes railway lines) on production, with a 1 per cent increase in that type of infrastructure increasing output by about 0.1 per cent (statistically significant at the 1 per cent level). The results show the opposite impact from roads, bridges, and tunnels, with a 1 per cent increase in that type of infrastructure corresponding to a 0.2 per cent decrease in output (statistically significant at the 1 per cent level).Results also indicate a small and negative impact of marine engineering infrastructure on production (-0.02 per cent), but only statistically significant at the 10 per cent level.

We then perform a Hausman test, robust to spatial and temporal dependence, and find that our model should be estimatedwith fixed effects in order to ensure consistency. The results from the fixed effects regression are presented in Column 2 of Table 1 and are slightly different from the pooled OLS model.First, the coefficient estimate on the employment variable is close to unity and is much larger than its income share. Evans and Karras (1994) found a similar result in their fixed effect analysis. They suggest that this may be due to a simultaneity bias, where firms plan their employment needs in anticipation of the error term. As a result, the estimate on hours worked is biased upward.

The coefficient estimate on highways remains negative, but is lower at 0.08 per cent, and only statistically significant at the 10 per cent level. The coefficient on railways with fixed effects is not statistically significant. Similarly, the coefficient on marine engineering infrastructure also becomes not statistically significant. Baltagi and Pinnoi (1995) also note that the fixed effects model estimates the short-run impact while the pooled OLS model estimates the long-run impact. If we follow this reasoning, the long-term impact of railways on production would be positive and highly statistically significant while its short-term impact would be close to zero.

As a robustness check, we also estimate the model using feasible generalized least squares (FGLS) which allows estimation in the presence of AR(1) autocorrelation, cross-sectional correlation as well as heteroskedasticity (Column 3 of Table 1). The order of magnitude of the estimates on hours worked and private capital are aligned with their income share. The coefficient estimate on highway remains negative and is statistically significant at the 1 per cent level. The magnitude of that coefficient indicates that a 1 per cent increase in that type of transport infrastructure would decrease output by about 0.05 per cent. The coefficient on other transportation infrastructure (including railway lines) is positive and statistically significant (at the 5 per cent level), and indicates that a 1 per cent increase in that type of infrastructure would increase output by about 0.05 per cent. For marine engineering infrastructure, the coefficient is positive but only statistically significant at the 10 per cent level. However, according to Beck and Katz (1995), FGLS underestimates standard errors when used on finite samples and complex error structures. In other words, the coefficients obtained from the FGLS regressions might not be as precise as our results imply.

Finally, we estimate the equation using Prais-Winsten regressions as an alternative to FGLS. This method controls for heteroskedasticity in the error term, as well as error terms that are contemporaneously correlated across panels (i.e., provinces). Since provinces are highly connected, this alternative method might provide better estimates. We estimate this regression first without province fixed effects. We find in this case that the coefficient estimates remain fairly similar to the FGLS model, although the coefficient on marine engineering infrastructure is no longer significant. When we introduce province fixed effects,[3] the coefficient on private capital drops to almost zero and is no longer statistically significant (in similar fashion to the estimates using the fixed effects with Driscoll-Kraay standard errors). This estimation gives a similar negative coefficient on roads, highways and bridges (-0.09 per cent), but is only statistically significant at the 10 per cent level. The estimate on other transport infrastructure (including railways) also remains similar to the equation without fixed effects but is no longer statistically significant.

Overall, these base results suggest that road infrastructure has a negative impact on output in Canada over the period of the study, while railways might have a positive impact, or at least that the category that includes railways does. The results on marine infrastructure are inconclusive. The inclusion of fixed effects in the model does lower the magnitude of the coefficients, indicating that provincial characteristics might play a role in the relationship between transportation infrastructure and output.

[3] The Prais-Winsten regressions are estimated using xtpcsein Stata, which does not explicitly include a fixed effects option. Instead, we include a dummy variable for each province.

7.2 Static production function in differences

We test for a unit root both in levels and in first differences and find that our series are most likely I(1).To correct for this non-stationarity, we estimate some of the specifications of the production function ingrowth rates (without fixed effects). Unfortunately, this technique may also eliminate the long run relationship among our variables.

Table 2: Results using a first-differenced production function, with Δln(GDP) as Dependent Variable

	Pooled OLS	FGLS	Prais Winsten
Non-transp. K	0.0515	0.0802*	0.0438
	(1.01)	(2.39)	(0.51)
Hours worked	0.414*	0.302***	0.369**
	(2.48)	(6.46)	(2.79)
Roads	-0.0744	-0.0274	-0.0612
	(-1.37)	(-1.61)	(-1.53)
Other (inc. rail)	0.0268	0.0316*	0.0315
	(0.99)	(2.16)	(0.82)
Marine	-0.0391	-0.00751	-0.0282
	(-1.62)	(-0.41)	(-0.54)
Unemployment	-0.0730**	-0.0685***	-0.0766***
	(-2.93)	(-8.73)	(-4.54)
Constant	0.0155***	0.0171***	0.0165***
	(4.08)	(13.29)	(4.69)
N	210	210	210

Note: Standard errors in parentheses. Independent variables are included in logarithmic form.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

The results of these regressions are shown in Table 2. The coefficient estimates do not vary greatly from one specification to the other. The estimate on highways remains negative and of similar magnitudes to the estimates in levels. However, they are not estimated precisely, and they are not statistically significant. Similarly, the coefficients on other transportation infrastructure (which includes railway lines) remain positive and of similar magnitude to the regression in levels. For this variable, the coefficient is statistically significant only in one equation (using FGLS), but only at the 10 per cent level. For marine engineering infrastructure, coefficients remain negative in every equation but never statistically significant.

7.3 Dynamic production function

We also estimate a dynamic production function that considers the simultaneity between output and transportation infrastructure. The static Cobb-Douglas production function does not account for the dynamic adjustments betweentransportation infrastructure and output. Therefore, we add a lag of the dependent variable to the model, as well as lags of some of the independent variables. We first estimate this augmented model with OLS (both a pooled OLS and a fixed effects model). However, as mentioned earlier, it is well known that pooled OLS and fixed effects dynamic panel models are prone to biases when including lags of the dependent variable, and most likely inconsistent. As in Jiwattanakulpaisarn*et al.* (2011), we thus also estimate the model using a system GMM model.

We estimate this model treating all variables as endogenous except for unemployment rate, which we assumed to be exogenous. [4] We make this simplification to limit the number of instruments given our small sample. For the same reason, we estimate three different system GMM models: one for each category of transportation infrastructure.

Unfortunately, system GMM assumes that there is no correlation across entities in the error term, which is most likely present in our case as we mentioned previously. Moreover, this model works best when the time dimension is relatively small compared to the number of entities. In our case, the time dimension is much larger than the number of provinces.

Table 3 shows the results of these estimations. First, as expected, past output strongly predicts current output in all estimations. Looking at road infrastructure, the coefficient estimates from the dynamic panel models are consistent from one specification to the other, and never indicate a statistically significant relationship. Using these estimates to compute long- run and short-run elasticity of output, we find that the long-run elasticity of output with respect to road infrastructure, based on the system GMM model, is positive (0.07) while the short run elasticity is negative (-0.07). These estimated elasticities, especially the long-run elasticity, are different from those estimated with OLS coefficients.

For other transportation infrastructure (including railway lines), the long-run elasticity of output based on the system GMM model is large and positive (0.27), while it is even larger for the short-run elasticity of output (0.75). For marine engineering infrastructure, the coefficient estimates on private capital is negative and statistically significant, which raises concerns over the validity of the specification.

Overall, the results on the category that includes railways are consistent with our previous estimations,indicating a positive relationship. The results on road infrastructure show a negative relationship as in previous estimates, but they are not as precisely estimated and thus not statistically significant. Regarding marine infrastructure, however, the results of the dynamic regressions indicate a strong positive relationship that is statistically significant. In our static regression models,we only found weak relationships.

[4] We estimate the System GMM model using the command xtabond2 in Stata.

Table 3: Results using a Dynamicproduction function, with ln(GDP) as the dependent variable

	Pooled OLS	Fixed Effects	System GMM	System GMM	System GMM
Y(t-1)	0.926***	0.855***	0.689***	0.633***	0.512***
	(30.52)	(19.03)	(12.18)	(15.48)	(8.37)
K	0.0479	-0.00342	0.196*	0.243**	-0.443**
	(0.59)	(-0.04)	(2.10)	(2.79)	(-2.91)
K(t-1)	-0.0173	0.0142	-0.0833	-0.150	0.618***
	(-0.20)	(0.16)	(-0.85)	(-1.59)	(3.83)
L	0.444**	0.392	0.733***	0.842***	0.892***
	(2.94)	(2.06)	(8.98)	(10.28)	(8.63)
L(t-1)	-0.392*	-0.276	-0.552***	-0.670***	-0.665***
	(-2.66)	(-1.71)	(-6.64)	(-7.99)	(-6.64)
H	-0.0523	-0.0369	-0.0230		
	(-1.24)	(-0.83)	(-0.39)		
H(t-1)	0.0320	0.0520	0.0461		
	(0.73)	(1.07)	(0.91)		
R	0.0360	0.0288		0.277***	
	(1.59)	(0.99)		(4.72)	
R(t-1)	-0.0212	-0.0362		-0.179***	
	(-0.86)	(-1.26)		(-3.48)	
M	-0.0161	0.00267			0.415***
	(-0.52)	(0.07)			(5.08)
M(t-1)	0.0131	-0.0146			-0.367***
	(0.39)	(-0.37)			(-4.65)
U	-0.0628*	-0.0783**	-0.00650	0.0209**	-0.153***
	(-2.57)	(-3.33)	(-0.43)	(3.14)	(-5.35)
U(t-1)	0.0826**	0.0786**			
	(3.57)	(3.25)			
Constant	0.409*	1.026	1.572***	2.521***	3.280***
	(2.51)	(1.36)	(4.08)	(9.12)	(8.04)
N	210	210	210	210	210
Long-run elasticities with respect to output					
H	-0.27	0.10	0.074		
R	0.20	-0.051		0.27	
M	-0.04	-0.082			0.098

Note: Standard errors in parentheses. Columns 1 and 2 report Driscoll-Kraay standard errors estimated using xtscc in Stata. Columns 3 to 5 are estimated using xtabond2 in Stata. Variables are abbreviated as such: Y is output, K is non-transportation capital, L is hours worked, H is highways and roads, R is other including railways, M is marine infrastructure, U is unemployment.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

7.4 Static multifactor productivity function

Finally, we estimate an alternative equation where multifactor productivity growth is the dependent variable. The independent variables are the same as in the production function estimated in growth rates. We report estimates from the pooled OLS model using Driscoll-Kraay standard errors, FGLS model as well as the alternative Prais-Winsten model with corrections for errors that are correlated across panels.

Table 4: Results from a differenced regression with Δln(MFP) as thedependent variable

	Pooled OLS	FGLS	Prais Winsten
Non-transp. K	-0.351***	-0.332***	-0.403***
	(-5.29)	(-7.85)	(-3.41)
Hours worked	-0.106	-0.286***	-0.205
	(-0.48)	(-4.95)	(-1.16)
Roads	-0.0948	-0.0506*	-0.0796
	(-1.41)	(-2.39)	(-1.49)
Other (inc. rail)	0.00525	-0.00810	0.00915
	(0.14)	(-0.38)	(0.17)
Marine	0.0303	0.0432	0.0472
	(0.97)	(1.83)	(0.66)
Unemployment	-0.0901*	-0.0966***	-0.105***
	(-2.85)	(-8.86)	(-4.68)
Constant	0.0126*	0.0131***	0.0150**
	(2.73)	(7.41)	(3.24)
N	200	200	200

Note: Standard errors in parentheses. Independent variables are included in logarithmic form.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

The results of these estimations are shown in Table 4. As in the production function estimates, the coefficient estimates on road infrastructure is negative in each specification, but is only statistically significant in the FGLS regression, and only at the 10 percent level. This indicates a negative but weak relationship between roads and highways and multifactor productivity. For other transportation infrastructure (including railway lines), the coefficients are very small, oscillating around zero. Therefore, while this type of infrastructure positively affects labour productivity, it seems that it has no effect on multifactor productivity. For marine engineering infrastructure, the coefficient estimates are positive but non-statistically different from zero.

Looking back at all of our results for the business sector, the coefficient estimates on road infrastructure appear robust across many specifications and suggests that the impact of additional highway and road infrastructure might not support business sector productivity. Cost-benefit analysis for specific projects might still provide positive estimates of impact from specific road improvements. In most results except those on multifactor productivity, railway lines (a significant component of other transportation infrastructure) appear to have a small but positive impact on business sector production. For marine engineering infrastructure, such as seaports, the evidence is mixed with no definitive conclusions. It is unlikely thatinvestment in transportation infrastructure would be detrimental to production. But it is possible that at the macro level, investment in highways and marine infrastructure does not translate into significant impact on production.

7.5 Industry specific coefficient estimates

Some industries might use a larger share of transportation services, and might therefore benefit more from additional investment in transportation infrastructure. The transportation and warehousing industry, although accounting for only 4.5% of gross domestic product in 2016, used 28% of transportation services provided as intermediate use. The transportation industry also enables economic activities in other industries. The manufacturing industry was the second largest user of transportation services, with 26%, followed by the wholesale industry, with 8%. Finance and retail trade industries used 5% and 4% of total intermediate use of transportation services, respectively. Due to this discrepancy in usage rates, we also estimate the static and dynamic production functions as well as the multifactor productivity function for different industries.

Table 5: Results using the Static Production Function Model in Levels Estimated using a Pooled OLS model, with ln(GDP) as Dependent Variable, for a Selection of Industries

	Transportation	Manufacturing	Construction	Retail Trade	WholesaleTrade
Non-transp. K	0.232***	0.164***	0.164	0.355***	0.248*
	(12.26)	(11.67)	(1.70)	(8.30)	(2.47)
Hours worked	0.481***	0.710***	1.120***	0.541***	0.679***
	(13.17)	(24.17)	(15.70)	(9.57)	(5.52)
Roads	0.179***	0.361***	-0.288***	-0.0157	0.142*
	(4.10)	(5.41)	(-4.49)	(-0.75)	(2.24)
Other (inc. rail)	0.150***	0.0214	0.0901***	0.118***	0.0815
	(4.99)	(0.54)	(6.43)	(5.83)	(1.99)
Marine	-0.0201***	-0.227***	-0.0475	0.00171	-0.0851*
	(-4.04)	(-22.29)	(-1.62)	(0.11)	(-2.38)
Unemployment	-0.120***	-0.180**	0.107**	0.000984	-0.179**
	(-5.09)	(-3.69)	(2.94)	(0.06)	(-3.09)
Trend	0.000540	-0.00636*	-0.00540	0.0113***	0.0136***
	(0.28)	(-2.19)	(-1.99)	(7.48)	(4.20)
Constant	4.584***	3.652***	3.621***	4.755***	2.760***
	(19.76)	(35.83)	(9.92)	(14.88)	(4.78)
N	220	220	220	220	220

Note: Standard errors in parentheses. Independent variables are included in logarithmic form.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

Results are shown in Table 5 for the pooled OLS model, while detailed results are available in the Appendix. For the transportation and warehousing sector, we find a strong positive impact of railway lines on production (ranges from 0.14 to 0.19 from one specification to the other, with a coefficient of 0.18 in the pooled OLS model). For highways, the coefficient estimate appears to be positive and statistically significant when estimated using the pooled OLS model (long run impact) but it is not statistically different from zero when using the fixed effects model (short run impact). The estimated impact of marine engineering is negative and statistically significant.

For the manufacturing sector, the coefficient estimate on highways from the pooled OLS model is positive and statistically significant (Column 2 of Table 5), but it is not statistically significant when we estimate the fixed effects model. For railway lines, the relationship is not statistically significant while itis negative for marine engineering infrastructure.

For the construction sector, the relationship between highways and production is negative and statistically significant in the pooled OLS model but is not statistically significant across all specifications. Similarly, the impact of railway lines on production is positive and significant in the pooled OLS model but is not statistically significant in other specifications. In this industry, marine infrastructure does not appear to impact output.

We also estimate these equations in differenced form. Table 6 presents these results. In the transportation industry, the estimated coefficient on highways is negative but not statistically significant, similar to the one estimated in the fixed effects model in levels. Using FGLS in differenced form, we also find a negative coefficient of similar magnitude, but significant at the 10 per cent level. [5] The coefficient estimate on railway lines is positive and statistically significant for that sector, but we do not find any statistically significant results on marine infrastructure.

In the manufacturing industry when we estimate the production function in the differenced form, the coefficient on highways is negative and non-statistically significant. However, estimating this differenced model using FGLS, we do find a statistically significant coefficient (at the 5 per cent level). In that sector, we find no impact of railways on productivity, while we find a small negative impact of marine infrastructure. That negative impact was also present in the model in levels.

In the construction industry in first differences, the coefficient estimates for all three categories of transportation infrastructure are positive but non-statistically significant. The same is true for the retail trade sector. However, in the wholesale trade sector, we do find a negative and statistically significant coefficient on marine infrastructure.

[5] Results fromthe FGLS regression are found in the Appendix.

Table 6: Results using the Static Production Function Model in Differences Estimated using a Pooled OLS model, with Δln(GDP) as Dependent Variable, for a Selection of Industries

	Transportation	Manufacturing	Construction	Retail Trade	Wholesale Trade
Non-transp. K	0.0101	0.0268	0.0263	0.126	0.119
	(0.21)	(0.31)	(0.56)	(1.85)	(1.73)
Hours worked	0.247***	0.392*	0.751***	0.109**	0.292*
	(5.13)	(2.83)	(11.00)	(3.25)	(2.80)
Roads	-0.0718	-0.145	0.0276	-0.0638	-0.0513
	(-0.89)	(-1.53)	(0.20)	(-1.03)	(-0.44)
Other (inc. rail)	0.117**	-0.0367	0.0305	0.0349	-0.00519
	(2.95)	(-0.55)	(0.40)	(1.09)	(-0.08)
Marine	0.0117	-0.154*	0.0634	-0.0517	-0.165*
	(0.19)	(-2.17)	(0.69)	(-1.04)	(-2.54)
Unemployment	-0.0621**	-0.178***	-0.0707	-0.0882***	-0.185***
	(-3.57)	(-4.59)	(-1.66)	(-4.18)	(-4.75)
Constant	0.0157*	0.0120*	0.00817	0.0250***	0.0183**
	(2.69)	(2.38)	(1.28)	(5.69)	(3.07)
N	210	210	210	210	210

Note: Standard errors in parentheses. Independent variables are included in logarithmic form.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

We also estimate the dynamic model using the industry-level data. The results of these regressions are included in the Appendix. In the transportation sector, the dynamic production function that includes fixed effects shows a negative impact from highways and roads, and a positive impact of other infrastructure including railway lines. The results on this type of infrastructure are in line with the static models. In manufacturing, we do not find significant coefficients on any type of transport infrastructure. In the construction sector, the results of the dynamic models indicate no impact of transportation infrastructure, which is in line with the results of the static fixed effects and differenced models. Similarly, in both retail and wholesale trade, we mostly do not find significant coefficients on transportation infrastructure in the dynamic models. For wholesale trade, the short-run (non-lagged) coefficient on marine infrastructure is negative and significant at the 10 per cent level. The coefficient is similar to the ones found in static models but estimated with lower precision.

Overall, our industry-level results do suggest that the impact of transport infrastructure might differ by industry. Our results are most conclusive in the transportation structure, especially regarding railways. However, looking at the results of the equation in levels only, transportation infrastructure seems to have the most impact outside of the transportation industry in the goods-producing industries such as manufacturing.

7.6 Alternative dataset

We also estimate the static models using an alternative dataset. The sample size is much smaller with only data ranging from 2009 to 2018 for ten provinces. However, transportation infrastructure is disaggregated at a more granular level which allows us to explore the relationship of railway lines, seaports and airports, which was not possible using the original dataset.

Table 7: Results using the Static Production Function Model in levels, with ln(GDP) as Dependent Variable, usingAlternative Dataset

	Pooled OLS	Fixed effects	FGLS	Prais- Winsten	Prais-Winsten with fixed effects
Non-transp. K	0.391***	-0.0125	0.389***	0.377***	0.00258
	(30.18)	(-0.44)	(164.67)	(12.21)	(0.06)
Hours worked	0.915***	0.689**	0.906***	0.608***	0.479**
	(15.35)	(4.44)	(126.22)	(6.99)	(3.26)
Roads	-0.242***	0.0566	-0.234***	-0.0707	0.112**
	(-22.79)	(1.15)	(-38.18)	(-1.33)	(3.07)
Railway lines	0.129***	0.00530	0.124***	0.0597*	-0.00337
	(8.96)	(0.68)	(24.30)	(2.36)	(-0.20)
Seaports	-0.0144***	-0.0122	-0.0144***	0.0173	-0.0215
	(-6.59)	(-1.21)	(-19.29)	(1.28)	(-1.70)
Airports	-0.180**	0.0210	-0.170***	-0.00254	0.0226
	(-3.49)	(1.07)	(-20.17)	(-0.05)	(0.86)
Unemployment	0.135**	-0.0297	0.127***	0.0181	-0.0618*
	(3.46)	(-1.02)	(18.65)	(0.59)	(-2.30)
Trend	0.00452*	0.0114***	0.00471***	0.00121	0.0115***
	(2.44)	(11.87)	(8.80)	(0.46)	(5.02)
Constant	10.05***	16.05***	9.998***	9.937***	18.91***
	(49.19)	(6.93)	(228.58)	(29.20)	(7.56)
N	100	100	100	100	100

Note: Standard errors in parentheses. Independent variables are included in logarithmic form.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

Results for the business sector output are presented in 7. In the pooled OLS regression (Column 1), we find that a negative and statistically significant (1 per cent level) coefficient for highways and roads of -0.24 per cent for every 1 per cent increase in infrastructure, a positive and statistically significant (1per cent level) coefficient for railways at 0.13 per cent, and a negative and statistically significant (1 per cent level) coefficient for seaports at -0.014 per cent. These results are similar to our results using the original dataset. Our new dataset, however, allows disaggregation of airports in a separate category. On that type of infrastructure, we find a negative and statistically significant (5 per cent level) coefficient of -0.18 per cent.

When we estimate the production function using a fixed effects model, the coefficient estimate on highways and roads becomes positive (and statistically significant when using the Prais -Winsten estimator in Column 5). This suggests that some time-invariant province-specific characteristics could affect the impact of the stock of highways on production. For example, provinces less densely populated might need a larger stock of highways for the same level of employment and private capital. The pooled OLS model, which does not account for province-specific characteristics, would then show that a larger stock of highways does not necessarily translate into more production. The fixed effects model focuses on within-province variation and shows that, when we only look within a specific province, an increased stock of highways and roads does in fact lead to a higher level of GDP, everything else fixed.

Table 8: Results using a first-differenced production function, with Δln(GDP) as Dependent Variable, using Alternative Dataset

	Pooled OLS	FGLS	Prais Winsten
Non-transp. K	0.131*	0.119***	0.126
	(3.09)	(5.71)	(1.48)
Hours worked	0.193	0.241***	0.167
	(1.03)	(6.28)	(1.03)
Roads	0.0933	0.0834***	0.113*
	(1.24)	(4.78)	(2.22)
Railway lines	0.000712	0.00319	0.00108
	(0.03)	(0.54)	(0.04)
Seaports	-0.00896	-0.0123***	-0.0153
	(-0.94)	(-4.31)	(-0.97)
Airports	-0.00890	-0.00245	-0.0167
	(-0.28)	(-0.25)	(-0.46)
Unemployment	-0.0895*	-0.0795***	-0.0900**
	(-2.86)	(-9.81)	(-3.25)
Constant	0.0116***	0.0116***	0.0109*
	(5.37)	(11.24)	(2.49)
N	90	90	90

Note: Standard errors in parentheses. Independent variables are included in logarithmic form.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

Looking at railway lines instead, we find that they positively affect production. As mentioned above, the coefficient on that type of infrastructure is positive and statistically significant in the pooled OLS regression. It is also significant in the FGLS regression and Prais-Winsten without fixed effects. Notably, the coefficient in the Prais-Winsten regression is much lower than in the pooled OLS and FGLS regressions (and only statistically significant at the 10 per cent level), at about 0.06 per cent vs. about
0.12 per cent. This indicates that accounting for the correlation of error terms across panels might be important. In fact, there might be an important spatial spillover aspect in the relationship between railways and productivity: connections across provinces are important. Looking at the coefficients on rail in the fixed effects models, we find that including fixed effects reduces the coefficient to a value close to zero. In other words, variations in railway stocks within provinces do not affect productivity.

For marine engineering infrastructure, we find a negative and statistically significant (at the 1 per cent level) coefficient in both the pooled OLS and FGLS regression. Both coefficients are small and translate in a reduction of output of 0.01 per cent for an increase of 1 per cent in that type of infrastructure. Again, we find nonsignificant effect when adding fixed effects. Finally, while we find a negative impact of airports in the pooled OLS and FGLS regression, the effect is not significant in regressions with fixed effects, orin the Prais-Winsten regression.

Table 9: Results froma differenced regression with Δln(MFP) as thedependent variable, using AlternativeDataset

	Pooled OLS	FGLS	Prais Winsten
Non-transp. K	-0.263***	-0.254***	-0.312***
	(-6.29)	(-7.94)	(-3.33)
Hours worked	-0.438	-0.332***	-0.502**
	(-1.86)	(-4.40)	(-2.58)
Roads	0.129	0.0489	0.145*
	(1.71)	(1.64)	(2.17)
Railway lines	0.00476	-0.00893	-0.00673
	(0.19)	(-0.95)	(-0.23)
Seaports	0.00207	-0.00989	-0.0000428
	(0.17)	(-1.13)	(-0.00)
Airports	-0.0352	-0.0525**	-0.0339
	(-0.82)	(-3.17)	(-0.67)
Unemployment	-0.138***	-0.111***	-0.146***
	(-6.13)	(-7.75)	(-4.20)
Constant	0.00679*	0.0113***	0.00810
	(2.52)	(4.55)	(1.51)
N	80	80	80

Note: Standard errors in parentheses. Independent variables are included in logarithmic form.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

When we estimate the production function in differences (Table 8) as well as using multifactor productivity growth as the dependent variable (Table 9), we still find a positive and statistically significant coefficient on the stock of highways and roads (in the three models). We also find a statistically significant negative impact of marine engineering infrastructure when using FGLS in difference form.

We also look at industry-specific estimates. Table 10 presents the main results using pooled OLS and fixed effects regressions per industry, and the full results are available in the Appendix. For the transportation and warehousing sector, we find that the impact of highways and roads on output is positive when we estimate the pooled OLS model. However, it is negative in the fixed effects model. For railway lines, the impact on output is positive whether we estimate the production function with pooled OLS or with the fixed effects model. However, the magnitude of the coefficient is much lower inthe fixed effects regression. This is aligned with the results from the original dataset.

Table 10: Results using the Static Production Function Model in levels, with ln(GDP) as Dependent Variable, usingAlternative Dataset, and for a Selection of industries

Transportation			Manufacturing		Construction	
	Pooled OLS	Fixed Effects	Pooled OLS	Fixed Effects	Pooled OLS	Fixed Effects
Non-transp. K	0.295***	0.208***	0.0498	0.0671*	0.106	0.00808
	(15.55)	(8.03)	(1.67)	(2.27)	(0.72)	(0.08)
Hours worked	0.425***	0.0875	0.737***	0.712***	1.313***	0.869***
	(9.30)	(0.94)	(60.34)	(6.95)	(12.82)	(11.19)
Roads	0.129**	-0.201*	0.316***	0.0412	-0.206*	-0.0430
	(3.35)	(-2.93)	(10.79)	(0.91)	(-2.85)	(-0.56)
Railway lines	0.196**	0.0519**	0.0364	-0.0849***	0.0570	0.0421
	(4.49)	(3.32)	(0.73)	(-6.74)	(1.53)	(1.24)
Seaports	0.00178	-0.0118	-0.125***	-0.0564***	-0.0192*	0.0456
	(0.17)	(-0.53)	(-15.23)	(-7.42)	(-2.38)	(1.53)
Airports	-0.0613	0.00837	0.00888	0.0836	-0.197*	0.0899
	(-1.14)	(0.24)	(0.13)	(1.33)	(-2.38)	(1.46)
Unemployment	-0.0463	-0.0216	-0.158**	-0.0942*	-0.0666	-0.163***
	(-1.54)	(-1.93)	(-4.29)	(-2.92)	(-1.33)	(-5.51)
Trend	-0.000382	0.0227***	0.0155***	0.0236***	0.000987	-0.00538
	(-0.16)	(5.40)	(4.83)	(14.43)	(0.17)	(-0.91)
Constant	8.794***	25.96***	8.344***	14.50***	10.14***	10.09**
	(19.90)	(9.68)	(18.62)	(5.19)	(25.93)	(4.23)
N	100	100	100	100	100	100

Note: Standard errors in parentheses. Independent variables are included in logarithmic form.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

For the manufacturing sector, the impact of highways on output is positive in the pooled OLS model, but not statistically significant in the fixed effects model. The impact of railway lines is not statistically significant in the pooled OLS model, and actually negative in the fixed effects model (and statistically significant at the 1 per cent level). That being said, the negative coefficient is not statistically significant if we estimate the fixed effects model using the Prais-Winsten regression, and we find a positive and statistically significant coefficient in the FGLS regression. Therefore, we remain cautious in our conclusions regarding the impact of railway stock in the manufacturing sector. Looking at marine infrastructure, we find negative and statistically significant coefficients in both models (pooled OLS and fixed effects). Looking at airports, both the pooled OLS and fixed effects model find no statistically significant coefficient.[6]

For the construction sector, we find a negative coefficient on roads and highways of similar magnitude to the business sector, but only statistically significant at the 10 per cent level. In the fixed effects model, the coefficient is not statistically significant. Looking at railroads, we do not find an effect in either model. We do find a negative coefficient for marine infrastructure in the pooled OLS regression, but it is only statistically significant at the 10 per cent level. Similarly, the coefficient for airports in the pooled OLS regression is negative but only statistically significant at the 10 per cent level.

[6] The first difference model shown in the Appendixes well as the FGLS model in levels do show a positive coefficient.

Table 11: Results froma differencedregressionwith Δln(MFP) as thedependent variable, using Alternative Dataset, and for a Selection of Industries

	Transportation	Manufacturing	Construction
Non-transp. K	-0.403**	-0.0710	-0.109
	(-4.61)	(-0.72)	(-0.92)
Hours worked	-0.167*	-0.544	-0.140
	(-3.29)	(-2.36)	(-2.25)
Roads	-0.0768	0.0116	0.269*
	(-1.02)	(0.10)	(2.41)
Railways	-0.0323	-0.0726*	0.0108
	(-0.86)	(-3.06)	(0.24)
Seaports	0.0135	-0.0125	0.0359
	(1.74)	(-0.87)	(0.75)
Airports	0.0476	0.00410	0.0859
	(1.69)	(0.04)	(1.37)
Unemployment	-0.0640**	-0.157***	-0.226**
	(-5.09)	(-6.53)	(-3.59)
Constant	0.0203***	0.0269***	-0.00749
	(5.87)	(10.89)	(-0.67)
N	80	80	80

Note: Standard errors in parentheses. Independent variables are included in logarithmic form.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

Table 11 shows the sectoral impact of transport infrastructure on MFP instead. Briefly, we see that the results are not significant for most industries for most types of capital. The exception is road infrastructure in the construction sector, where an increase in infrastructure is associated with a positive increase in MFP (only statistically significant at the 10 per cent level in the pooled OLS regression, but also significant and of similar magnitude in the FGLS and Prais-Winsten regressions).

8 CONCLUSIONS

This paper studies the relationship between transportation infrastructure and output and productivity. We estimate different specifications of a static Cobb-Douglas production function (in levels and indifferences). Suspecting that investment in infrastructure could affect output with a lag, and to control for the possible non-stationarity in output time series, we also estimate a dynamic production function that includes lags of the dependent variable and our variables of interest. We do so with OLS and System GMM. In order to further explore the relationship between transportationinfrastructure and productivity, we also estimate a multifactor productivity growth function. Finally, since the original dataset did not allow to disaggregate transportation infrastructure sufficiently, we also estimate the static functions using an alternative data set that allows a more granular disaggregation but covers a shorter time period. This allowed us to estimate the impact of railway lines, seaports and airports.

Table 11: Summary table for results from the Static Production Function Model estimated in levels with the Pooled OLS, with ln(GDP) as Dependent Variable

	Business	Transp.	Manu.	Constr.	Retail tr.	Wholesale tr.
Roads	-0.20	0.18	0.36	-0.29	-0.02	0.14
Roads*	-0.24	0.13	0.32	-0.21		
Other (incl. railways)	0.10	0.15	0.02	0.09	0.12	0.08
Railway lines*	0.13	0.20	0.04	0.06		
Marine	-0.02	-0.02	-0.23	-0.05	0.00	-0.09
Seaports*	-0.01	0.00	-0.13	-0.02		
Airports*	-0.18	-0.06	0.01	-0.20		

*Using alternative dataset

Looking at the impact of highways first, we find that for the period spanning from 1997 to 2018 (i.e. theoriginal dataset), a higher stock of highways does not translate into higher production for the business sector, both when we account and don't account for province-specific effects. However, when using the alternative dataset, which ranges from 2009 to 2018, it appears that the impact is positive and statistically significant, but only when we account for province-specific characteristics. It is possible that the time period used in our estimation could have an impact on the coefficient estimates, which is why your results differ from one dataset to the other.

Using the coefficient estimates from the dynamic production function, we also find that the long run elasticity of highways is positive (0.07 to 0.10), which is consistent with, although slightly higher than, what Jiwattanakulpaisan *et al.* (2012) found in their research. Overall, our results on road infrastructure are not very conclusive, which is more in line with the more recent literature, as opposed to the earlier findings of Aschauer and others.

We then look at the impact of railways. In the first dataset, the coefficient estimates on other transportation infrastructure (which includes railway lines) align with the coefficient estimates on railway lines from the alternative dataset which is reassuring and confirms that other transportation infrastructure was a good proxy for railway lines. The coefficient estimates remain positive across most specifications in the business sector. Moreover, the long run elasticity of output with respect to railway lines is statistically significant and quite large (0.27). For this type of infrastructure, then, our results are more conclusive and point to a positive impact of railways on output and productivity.

For the stock of marine engineering infrastructure, coefficient estimates are mostly non-statisticallysignificant and oscillate between small positive and negative values. Moreover, the results from the system GMM model are most likely unreliable as the coefficient estimate on private capital is large and negative, unlike any other specifications.

In our industry-specific analysis, we find a positive and robust impact of railway lines on production in the transportation and warehousing sector. Using the original dataset, the coefficient estimates are positive and statistically significant across specifications. The relationship also appears robust to the use of the alternative dataset. Moreover, the long run elasticity of output with respect to railway lines in the transportation sector is quite large (0.10 to 0.17). Road infrastructure also appears to have a positive impact on production when we do not account for province-specific characteristics. It is not surprising that the transportation and warehousing sector would benefit from improvements in those two categories of transport infrastructure.

In the manufacturing sector, road infrastructure appears to have a positive impact on production (based on most specifications) while marine engineering construction would translate into lower production.

This suggests a positive association between additional stock of highways and roads and production in the manufacturing sector but the opposite association with the stock of marine construction.

In the construction sector, the coefficient estimates on highways indicate a negative relationship between that type of infrastructure and output. However, we do find coefficients in the multifactor productivity growth function that are positive and mostly statistically significant for both the original and alternative dataset. We find the same result when we estimate the static production function in first differences as well as the dynamic production function. The coefficient estimates on railway lines also remain positive across specifications and datasets. Those results suggest that the construction sector would benefit from a larger stock of highways and railway lines.

While our results are sometimes contradictory between specifications, or often not statistically significant, this analysis brings some light on infrastructure needs at the aggregate business level as well as at the sector-specific level in Canada. It does so using two different datasets over two different time periods. Our results are most conclusive regarding railway infrastructure, and indicate that the association between transport infrastructure and output can vary widelybetween sectors. Further research could potentially bring some light on some of the incongruities we found. For example, we could estimate a translog production function, or take a cost function approach which would allow to verify some of the results we obtained here. This would also give us a better understanding the substitution and complementarity relationship between the different inputs. Finally, we could also explore the impact of transportation infrastructure on other variables such as employment.

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Appendix Table 1: Manufacturing Sector - Results using the Static Production Function Model in levels, with ln(GDP) as Dependent Variable

	Pooled OLS	Fixed Effects	FGLS	Prais Winsten	Prais Winsten with fixed effects
Non-transp. K	0.164***	0.110*	0.161***	0.159***	0.0356
	(11.67)	(2.75)	(6.75)	(5.49)	(1.46)
Hours worked	0.710***	0.692***	0.801***	0.799***	0.555***
	(24.17)	(7.88)	(30.62)	(19.43)	(7.12)
Roads	0.361***	0.104	0.158***	0.155*	-0.0750
	(5.41)	(1.45)	(3.95)	(2.38)	(-1.15)
Other (inc. rail)	0.0214	0.0116	0.0848***	0.0877**	0.0490
	(0.54)	(0.27)	(4.37)	(2.89)	(1.05)
Marine	-0.227***	-0.0447	-0.191***	-0.191***	-0.117*
	(-22.29)	(-1.51)	(-11.93)	(-8.42)	(-2.27)
Unemployment	-0.180**	-0.114	-0.123***	-0.129***	-0.138***
	(-3.69)	(-1.89)	(-5.76)	(-3.92)	(-4.16)
Trend	-0.00636*	0.00714**	0.00191	0.00318	0.0102***
	(-2.19)	(3.00)	(1.23)	(1.27)	(4.01)
Constant	3.652***	6.105*	3.516***	3.513***	11.93***
	(35.83)	(2.39)	(22.67)	(16.23)	(5.46)
N	220	220	220	220	220

Note: Standard errors in parentheses. Independent variables are included in logarithmic form. Columns 1 and 2 report Driscoll-Kraay standard errors estimated using xtscc in Stata. Column 3report errors corrected for autocorrelation estimated using xtgls in Stata. Column 4 and 5 report errors estimated using xtpcse in Stata.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

Appendix Table2: Transportation Sector - Results using the Static Production Function Model in levels, with ln(GDP) as Dependent Variable

	Pooled OLS	Fixed Effects	FGLS	Prais Winsten	Prais Winsten with fixed effects
Non-transp. K	0.232***	0.0679	0.165***	0.167***	0.0645*
	(12.26)	(1.64)	(10.99)	(7.03)	(2.09)
Hours worked	0.481***	0.422***	0.539***	0.562***	0.397***
	(13.17)	(10.18)	(21.97)	(12.96)	(8.78)
Roads	0.179***	-0.117	0.157***	0.125**	-0.0963
	(4.10)	(-1.84)	(6.94)	(2.94)	(-1.85)
Other (inc. rail)	0.150***	0.139***	0.179***	0.190***	0.138***
	(4.99)	(6.09)	(8.90)	(5.77)	(3.59)
Marine	-0.0201***	-0.0475*	-0.0256*	-0.0314	-0.00886
	(-4.04)	(-2.14)	(-2.06)	(-1.59)	(-0.31)
Unemployment	-0.120***	-0.0143	-0.0614***	-0.0644*	-0.0249
	(-5.09)	(-0.38)	(-4.20)	(-2.34)	(-1.05)
Trend	0.000540	0.0131***	0.00451**	0.00342	0.0126***
	(0.28)	(9.04)	(3.13)	(1.36)	(6.24)
Constant	4.584***	12.97***	4.538***	4.554***	11.94***
	(19.76)	(14.78)	(26.32)	(17.21)	(10.83)
N	220	220	220	220	220

Note: Standard errors in parentheses. Independent variables are included in logarithmic form. Columns 1 and 2 report Driscoll-Kraay standard errors estimated using xtscc in Stata. Column 3report errors corrected for autocorrelation estimated using xtgls in Stata. Column 4 and 5 report errors estimated using xtpcse in Stata.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

Appendix Table 3: Construction Sector - Results using the Static Production Function Model in levels, with ln(GDP) as Dependent Variable

	Pooled OLS	Fixed Effects	FGLS	Prais Winsten	Prais Winsten with fixed effects
Non-transp. K	0.164	0.112**	0.148***	0.131*	0.0764
	(1.70)	(2.90)	(3.72)	(2.14)	(1.68)
Hours worked	1.120***	0.836***	0.809***	0.850***	0.781***
	(15.70)	(19.60)	(16.06)	(12.48)	(16.46)
Roads	-0.288***	-0.183	0.0237	-0.0111	-0.122
	(-4.49)	(-1.86)	(0.45)	(-0.14)	(-1.60)
Other (inc. rail)	0.0901***	0.103	0.0685*	0.0868*	0.0782
	(6.43)	(2.01)	(2.20)	(2.18)	(1.51)
Marine	-0.0475	-0.0185	0.0131	0.00771	0.0109
	(-1.62)	(-0.50)	(0.49)	(0.22)	(0.23)
Unemployment	0.107**	-0.0767	-0.0831**	-0.0569	-0.0739*
	(2.94)	(-1.19)	(-2.72)	(-1.41)	(-2.00)
Trend	-0.00540	0.00184	-0.000768	-0.00152	0.00393
	(-1.99)	(0.82)	(-0.27)	(-0.41)	(1.36)
Constant	3.621***	6.571***	3.537***	3.453***	7.006***
	(9.92)	(4.84)	(9.82)	(7.38)	(5.69)
N	220	220	220	220	220

Note: Standard errors in parentheses. Independent variables are included in logarithmic form. Columns 1 and 2 report Driscoll-Kraay standard errors estimated using xtscc in Stata. Column 3report errors corrected for autocorrelation estimated using xtgls in Stata. Column 4 and 5 report errors estimated using xtpcse in Stata.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

Appendix Table 4: Retail sale sector - Results using the Static Production Function Model in levels, with ln(GDP) as Dependent Variable

	Pooled OLS	Fixed Effects	FGLS	Prais Winsten	Prais Winsten with fixed effects
Non-transp. K	0.355***	0.125**	0.339***	0.334***	0.140**
	(8.30)	(2.84)	(14.02)	(7.79)	(2.89)
Hours worked	0.541***	0.345***	0.420***	0.437***	0.169**
	(9.57)	(4.72)	(15.71)	(9.44)	(3.01)
Roads	-0.0157	0.0179	0.0951***	0.0651	-0.0420
	(-0.75)	(0.47)	(4.13)	(1.59)	(-0.87)
Other (inc. rail)	0.118***	0.0386	0.0912***	0.104***	0.0506
	(5.83)	(1.34)	(5.90)	(4.17)	(1.59)
Marine	0.00171	-0.0992***	0.0587***	0.0561**	-0.103***
	(0.11)	(-5.67)	(4.79)	(2.92)	(-4.02)
Unemployment	0.000984	-0.152***	-0.0625***	-0.0803***	-0.0996***
	(0.06)	(-4.61)	(-4.85)	(-3.33)	(-3.86)
Trend	0.0113***	0.0172***	0.0158***	0.0155***	0.0217***
	(7.48)	(13.14)	(16.61)	(7.63)	(10.00)
Constant	4.755***	12.99***	4.770***	4.826***	16.16***
	(14.88)	(9.43)	(27.19)	(18.07)	(12.67)
N	220	220	220	220	220

Note: Standard errors in parentheses. Independent variables are included in logarithmic form. Columns 1 and 2 report Driscoll-Kraay standard errors estimated using xtscc in Stata. Column 3report errors corrected for autocorrelation estimated using xtgls in Stata. Column 4 and 5 report errors estimated using xtpcse in Stata.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

Appendix Table 5: Wholesale trade sector - Results using the Static Production Function Model in levels, with ln(GDP) asDependent Variable

	Pooled OLS	Fixed Effects	FGLS	Prais Winsten	Prais Winsten with fixed effects
Non-transp. K	0.248*	-0.113	0.298***	0.319***	-0.00494
	(2.47)	(-1.29)	(8.08)	(5.20)	(-0.09)
Hours worked	0.679***	0.826***	0.568***	0.601***	0.497***
	(5.52)	(7.54)	(10.98)	(7.43)	(6.19)
Roads	0.142*	0.0250	0.241***	0.149	0.0653
	(2.24)	(0.30)	(4.60)	(1.78)	(1.08)
Other (inc. rail)	0.0815	0.00642	0.0656	0.0681	-0.0151
	(1.99)	(0.11)	(1.85)	(1.22)	(-0.34)
Marine	-0.0851*	-0.0652**	-0.0852**	-0.0627	-0.196***
	(-2.38)	(-2.84)	(-2.79)	(-1.48)	(-5.48)
Unemployment	-0.179**	-0.155**	-0.161***	-0.167***	-0.186***
	(-3.09)	(-3.16)	(-6.44)	(-4.19)	(-5.31)
Trend	0.0136***	0.0279***	0.0114***	0.0137***	0.0193***
	(4.20)	(7.61)	(4.43)	(3.75)	(8.38)
Constant	2.760***	7.126***	2.925***	2.996***	12.52***
	(4.78)	(4.80)	(15.14)	(9.77)	(8.98)
N	220	220	220	220	220

Note: Standard errors in parentheses. Independent variables are included in logarithmic form. Columns 1 and 2 report Driscoll-Kraay standard errors estimated using xtscc in Stata. Column 3report errors corrected for autocorrelation estimated using xtgls in Stata. Column 4 and 5 report errors estimated using xtpcse in Stata.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

Appendix Table 6 Manufacturing Industry - Results using a Dynamicproduction function, with ln(GDP) as the dependentvariable

	Pooled OLS	Fixed Effects	System GMM	System GMM	System GMM
Y(t-1)	0.918***	0.781***	0.0262	-0.116	0.445***
	(27.30)	(28.17)	(0.29)	(-1.15)	(7.12)
K	0.0524	0.0518	-0.0959	-0.218*	-0.0834
	(0.56)	(0.53)	(-1.34)	(-2.52)	(-1.13)
K(t-1)	-0.0367	-0.0122	0.164*	0.0955	0.136
	(-0.37)	(-0.13)	(2.21)	(1.11)	(1.90)
L	0.415**	0.384**	0.860***	0.817***	0.674***
	(3.35)	(3.47)	(10.94)	(9.14)	(9.86)
L(t-1)	-0.362*	-0.274*	-0.249**	0.0217	-0.162*
	(-2.84)	(-2.11)	(-3.17)	(0.21)	(-1.99)
H	-0.136	-0.0276	0.619***		
	(-1.76)	(-0.39)	(4.73)		
H(t-1)	0.162	0.116	-0.255*		
	(2.02)	(1.52)	(-2.15)		
R	-0.0679	-0.0335		1.478***	
	(-0.68)	(-0.36)		(7.63)	
R(t-1)	0.0831	-0.000293		-1.006***	
	(0.84)	(-0.00)		(-6.20)	
M	-0.219*	-0.0983			0.0646
	(-2.10)	(-1.02)			(0.71)
M(t-1)	0.196	0.0882			-0.139
	(1.90)	(0.90)			(-1.45)
U	-0.179***	-0.171***	-0.405***	-0.107***	-0.198***
	(-5.79)	(-7.39)	(-10.18)	(-5.06)	(-6.49)
U(t-1)	0.180***	0.190***			
	(6.32)	(8.32)			
Constant	0.322**	1.583	2.770***	4.473***	2.636***
	(3.77)	(1.08)	(9.74)	(10.80)	(8.42)
N	210	210	210	210	210

Note: Standard errors in parentheses. Columns 1 and 2 report Driscoll-Kraay standard errors estimated using xtscc in Stata. Columns 3 to 5 are estimated using xtabond2 in Stata. Variables are abbreviated as such: Y is output, K is non-transportation capital, L is hours worked, H is highways and roads, R is other including railways, M is marine infrastructure, U is unemployment.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

Appendix Table 7 Transportation Industry - Results usinga Dynamic productionfunction, withln(GDP) as the dependentvariable

	Pooled OLS	Fixed Effects	System GMM	System GMM	System GMM
Y(t-1)	0.930***	0.818***	0.789***	0.250**	0.745***
	(22.28)	(13.57)	(13.41)	(3.06)	(14.38)
K	0.0357	0.0804	0.0939**	0.149***	0.126***
	(0.72)	(1.06)	(2.67)	(3.97)	(3.57)
K(t-1)	-0.00821	0.0138	0.0375	0.0972**	0.0589
	(-0.16)	(0.21)	(1.14)	(2.63)	(1.82)
L	0.267***	0.260***	0.362***	0.549***	0.346***
	(4.85)	(4.18)	(6.71)	(9.24)	(4.89)
L(t-1)	-0.238***	-0.230***	-0.325***	-0.306***	-0.314***
	(-5.89)	(-5.05)	(-6.22)	(-6.11)	(-6.09)
H	-0.127	-0.154**	-0.149*		
	(-2.08)	(-3.00)	(-2.23)		
H(t-1)	0.142*	0.0980	0.182**		
	(2.57)	(1.74)	(2.85)		
R	0.0446	0.105*		0.615***	
	(0.85)	(2.18)		(6.17)	
R(t-1)	-0.0375	-0.0734		-0.381***	
	(-0.75)	(-1.44)		(-4.76)	
M	0.0569	0.0222			0.217**
	(0.78)	(0.35)			(2.88)
M(t-1)	-0.0641	-0.0726			-0.187*
	(-0.85)	(-1.32)			(-2.52)
U	-0.0757***	-0.0970***	-0.0225	-0.0356*	-0.0188
	(-4.87)	(-4.97)	(-0.81)	(-2.54)	(-0.65)
U(t-1)	0.0605**	0.0604**			
	(3.09)	(2.94)			
Constant	0.326	2.985*	1.364***	4.812***	1.759***
	(1.93)	(2.68)	(4.53)	(9.52)	(5.95)
N	210	210	210	210	210

Note: Standard errors in parentheses. Columns 1 and 2 report Driscoll-Kraay standard errors estimated using xtscc in Stata. Columns 3 to 5 are estimated using xtabond2 in Stata. Variables are abbreviated as such: Y is output, K is non-transportation capital, L is hours worked, H is highways and roads, R is other including railways, M is marine infrastructure, U is unemployment.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

Appendix Table 8 Construction Industry - Results using a Dynamic production function, with ln(GDP) as the dependentvariable

	Pooled OLS	Fixed Effects	System GMM	System GMM	System GMM
Y(t-1)	0.914***	0.690***	0.474***	0.404***	0.452***
	(35.85)	(11.95)	(8.09)	(6.60)	(7.34)
K	0.00453	0.0184	-0.137	-0.0163	-0.0813
	(0.11)	(0.39)	(-1.70)	(-0.19)	(-1.00)
K(t-1)	0.00533	0.0259	0.0712	-0.0215	0.188**
	(0.11)	(0.59)	(1.05)	(-0.30)	(2.91)
L	0.774***	0.815***	1.084***	1.126***	0.951***
	(12.28)	(11.87)	(16.76)	(18.17)	(14.39)
L(t-1)	-0.706***	-0.573***	-0.497***	-0.518***	-0.573***
	(-8.94)	(-5.09)	(-6.61)	(-6.97)	(-7.94)
H	0.132	0.0875	0.108		
	(0.87)	(0.57)	(0.80)		
H(t-1)	-0.153	-0.137	-0.0478		
	(-0.92)	(-0.85)	(-0.39)		
R	0.102	0.0656		-0.0454	
	(1.20)	(0.70)		(-0.37)	
R(t-1)	-0.0807	-0.0377		0.131	
	(-0.95)	(-0.45)		(1.12)	
M	0.0145	0.0910			0.106
	(0.14)	(0.90)			(0.85)
M(t-1)	-0.00516	-0.0775			-0.0707
	(-0.05)	(-0.74)			(-0.55)
U	-0.0625	-0.0463	-0.0163	0.0296	-0.186***
	(-1.62)	(-1.11)	(-0.66)	(1.72)	(-5.88)
U(t-1)	0.0615	0.0444			
	(1.55)	(1.06)			
Constant	0.408*	1.993	0.771**	1.416***	2.760***
	(2.30)	(2.06)	(2.71)	(4.71)	(6.77)
N	210	210	210	210	210

Note: Standard errors in parentheses. Columns 1 and 2 report Driscoll-Kraay standard errors estimated using xtscc in Stata. Columns 3 to 5 are estimated using xtabond2 in Stata. Variables are abbreviated as such: Y is output, K is non-transportation capital, L is hours worked, H is highways and roads, R is other including railways, M is marine infrastructure, U is unemployment.
Significance levels: *** p=0.01, ** p=0.05, * p=0.1

Appendix Table 9 Transportation Industry - Results usinga static productionfunction, withln(GDP) as the dependentvariable– alternative dataset

	Pooled OLS	Fixed effects	FGLS	Prais- Winsten	Prais-Winsten with fixed effects
Non-transp. K	0.295***	0.208***	0.293***	0.381***	0.207***
	(15.55)	(8.03)	(106.26)	(10.97)	(5.69)
Hours worked	0.425***	0.0875	0.433***	0.396***	0.145*
	(9.30)	(0.94)	(56.62)	(6.80)	(2.29)
Roads	0.129**	-0.201*	0.125***	0.146***	-0.0822
	(3.35)	(-2.93)	(18.99)	(3.77)	(-1.67)
Railway lines	0.196**	0.0519**	0.191***	0.0542*	0.0252
	(4.49)	(3.32)	(43.07)	(2.19)	(1.37)
Seaports	0.00178	-0.0118	0.000992	0.0230*	0.00670
	(0.17)	(-0.53)	(0.63)	(2.47)	(0.54)
Airports	-0.0613	0.00837	-0.0580***	0.0355	0.0404
	(-1.14)	(0.24)	(-13.84)	(0.90)	(1.28)
Unemployment	-0.0463	-0.0216	-0.0453***	-0.0931***	-0.0496*
	(-1.54)	(-1.93)	(-22.33)	(-3.36)	(-2.29)
Trend	-0.000382	0.0227***	0.0000187	-0.000986	0.0186***
	(-0.16)	(5.40)	(0.04)	(-0.32)	(5.95)
Constant	8.794***	25.96***	8.819***	7.360***	20.86***
	(19.90)	(9.68)	(163.36)	(20.36)	(12.31)
N	100	100	100	100	100

Appendix Table 10 Manufacturing Industry - Results usinga static production function, withln(GDP) as the dependentvariable– alternative dataset

	Pooled OLS	Fixed effects	FGLS	Prais-Winsten	Prais-Winsten withfixed effects
Non-transp. K	0.0498	0.0671*	0.0518***	0.0884	0.0106
	(1.67)	(2.27)	(6.78)	(1.59)	(0.35)
Hours worked	0.737***	0.712***	0.733***	0.741***	0.395***
	(60.34)	(6.95)	(139.18)	(10.92)	(3.50)
Roads	0.316***	0.0412	0.315***	0.278***	0.0481
	(10.79)	(0.91)	(68.51)	(3.87)	(0.93)
Railway lines	0.0364	-0.0849***	0.0336***	-0.0236	-0.0562
	(0.73)	(-6.74)	(7.62)	(-0.53)	(-1.76)
Seaports	-0.125***	-0.0564***	-0.123***	-0.106***	-0.0536**
	(-15.23)	(-7.42)	(-80.06)	(-6.52)	(-3.18)
Airports	0.00888	0.0836	0.0154**	0.119*	0.0370
	(0.13)	(1.33)	(2.88)	(2.39)	(0.86)
Unemployment	-0.158**	-0.0942*	-0.155***	-0.152**	-0.119***
	(-4.29)	(-2.92)	(-38.56)	(-2.92)	(-3.63)
Trend	0.0155***	0.0236***	0.0156***	0.0136*	0.0225***
	(4.83)	(14.43)	(20.37)	(2.48)	(6.02)
Constant	8.344***	14.50***	8.309***	6.979***	20.53***
	(18.62)	(5.19)	(90.87)	(8.38)	(7.42)
N	100	100	100	100	100

Appendix Table 11 Construction Industry - Results usinga static production function, with ln(GDP) as the dependentvariable– alternative dataset

	Pooled OLS	Fixed effects	FGLS	Prais-Winsten	Prais-Winsten with fixed effects
Non-transp. K	0.106	0.00808	0.0991***	0.132	-0.0518
	(0.72)	(0.08)	(10.20)	(1.09)	(-0.48)
Hours worked	1.313***	0.869***	1.314***	1.050***	0.929***
	(12.82)	(11.19)	(126.97)	(10.02)	(12.21)
Roads	-0.206*	-0.0430	-0.200***	-0.0851	0.0125
	(-2.85)	(-0.56)	(-29.99)	(-1.02)	(0.13)
Railway lines	0.0570	0.0421	0.0500***	-0.0241	0.0140
	(1.53)	(1.24)	(7.64)	(-0.52)	(0.27)
Seaports	-0.0192*	0.0456	-0.0168***	-0.0101	0.0285
	(-2.38)	(1.53)	(-8.73)	(-0.72)	(0.94)
Airports	-0.197*	0.0899	-0.188***	-0.00237	0.118
	(-2.38)	(1.46)	(-19.45)	(-0.03)	(1.57)
Unemployment	-0.0666	-0.163***	-0.0637***	-0.0246	-0.127**
	(-1.33)	(-5.51)	(-19.15)	(-0.50)	(-2.90)
Trend	0.000987	-0.00538	0.00152*	0.000462	-0.00527
	(0.17)	(-0.91)	(2.04)	(0.11)	(-0.68)
Constant	10.14***	10.09**	10.05***	9.519***	9.626***
	(25.93)	(4.23)	(101.38)	(22.08)	(3.58)
N	100	100	100	100	100

Appendix Table 12 Transportation Industry - Results using a static production function, with Δln(GDP) as the dependent variable – alternative dataset

	Pooled OLS with Driscoll-Kraay SE	FGLS	Prais Winsten
Non-transp. K	0.129*	0.113***	0.187**
	(2.78)	(9.50)	(3.23)
Hours worked	0.142*	0.135***	0.162*
	(2.88)	(5.76)	(2.56)
Roads	-0.0499	-0.0452**	-0.0129
	(-0.85)	(-3.07)	(-0.24)
Railway lines	0.0181	0.0229***	0.0134
	(0.58)	(3.65)	(0.54)
Seaports	0.0238*	0.0213***	0.0321*
	(2.51)	(6.23)	(2.11)
Airports	0.0588*	0.0532***	0.0675*
	(3.15)	(5.47)	(2.07)
Unemployment	-0.0642**	-0.0661***	-0.0699**
	(-4.32)	(-7.76)	(-3.28)
Constant	0.0195***	0.0211***	0.0146**
	(6.10)	(12.28)	(3.27)
N	90	90	90

Appendix Table 13 Manufacturing Industry- Results usinga static production function, with Δln(GDP) as the dependentvariable– alternative dataset

	Pooled OLS	FGLS	Prais Winsten
Non-transp. K	0.000110	0.00114	-0.0135
	(0.00)	(0.03)	(-0.24)
Hours worked	0.202	0.248***	0.131
	(1.16)	(8.84)	(1.26)
Roads	0.0187	0.00334	0.0846
	(0.25)	(0.24)	(1.15)
Railway lines	-0.0833*	-0.0906***	-0.0502
	(-2.37)	(-7.60)	(-1.02)
Seaports	-0.0293	-0.0217***	-0.0398
	(-2.22)	(-3.34)	(-1.66)
Airports	0.0617	0.0538***	0.0390
	(0.99)	(5.52)	(0.62)
Unemployment	-0.112*	-0.111***	-0.138***
	(-3.27)	(-14.16)	(-3.69)
Constant	0.0233***	0.0226***	0.0181**
	(8.31)	(23.32)	(3.06)
N	90	90	90

Appendix Table 14 Construction Industry - Results usinga static production function, with Δln(GDP) as the dependentvariable– alternative dataset

	Pooled OLS	FGLS	Prais Winsten
Non-transp. K	0.0640	-0.0558	0.00719
	(0.48)	(-0.72)	(0.05)
Hours worked	0.802***	0.856***	0.839***
	(16.15)	(13.63)	(7.43)
Roads	0.140	0.152*	0.161
	(0.95)	(2.22)	(1.23)
Railway lines	0.0395	0.0335	0.0342
	(0.91)	(1.03)	(0.56)
Seaports	0.0282	0.0413*	0.0324
	(0.62)	(2.43)	(0.76)
Airports	0.115*	0.0623	0.112
	(3.17)	(1.14)	(1.01)
Unemployment	-0.143	-0.205***	-0.122*
	(-1.75)	(-6.92)	(-2.27)
Constant	-0.0104	-0.00898	-0.0128
	(-0.93)	(-1.51)	(-1.08)
N	90	90	90