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Transportation infrastructure and child mortality: Subnational evidence for 22 developing countries

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Abstract

What prevents people from utilizing health services? This paper hypothesizes that transportation infrastructure, as measured by travel time to cities, improves population health. Combining data for travel times with information on child mortality for 290 sub-national regions in Sub-Saharan Africa and Asia for the years 2000 and 2015, we show that a 1 standard deviation reduction in travel times, within sub-national regions, is associated with 9.3 fewer child deaths per 1,000 live births. Using estimates from the literature on the statistical value of life in developing countries, a 1 standard deviation reduction in travel times generates gains equivalent to 1.8 – 4.4% of GDP. Our results are not driven by selection on unobservables or changes in economic development and population density. Instrumental variables support a causal interpretation of the results. The life-saving effects of transportation are larger where poverty is most dire and where political institutions are better functioning.

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1 Introduction

In the year 2019, circa 5.2 million children under 5 years old died from mostly treatable and preventable causes. Along these causes belong diarrhea, malaria, and pneumonia, all of which can be treated or even prevented with access to affordable interventions such as nutrition, safe water and immunization (World Health Organization (WHO), 2020). More than half of the global population is not able to obtain essential health services (World Bank, 2017). As can be indicated by these shocking numbers, battling poor health outcomes is an ongoing challenge for developing countries.

In order to obtain medical care, one must be able to physically access health services (Elek et al 2015). Thus, the transportation infrastructure matters crucially. In this paper, we ask whether improvements in transportation infrastructure, as measured by travel time to cities, are correlated with improvements in health outcomes, as proxied by child mortality. While the intrinsic importance of reducing child mortality cannot be overstated, child mortality data have also generally been considered a valuable proxy for population health at large, as epidemiologists and public health scholars have known at least since Murray (1988).

We combine data on child mortality and data on travel times to cities larger than 50,000 inhabitants, for 290 sub-national regions from 22 countries in Sub-Saharan Africa and South Asia (Appendix Table A1 lists all countries and sub-national regions). Our results show that, *within* sub-national regions, a 1 standard deviation reduction in travel time is associated with 9.3 fewer child deaths per 1,000 live births. Crucially, since we have data for travel time and child mortality at two points in time for each sub-national region (the years 2000 and 2015), we are able to control for region-specific, time-invariant unobserved heterogeneity, by including sub-national region fixed effects in our empirical specifications. Doing so also controls for country-specific fixed effects, as each country's fixed effect is a linear combination of the sub-national region dummies nested under each country. Our empirical approach thus allows us to examine, within a given sub-national region, whether improvements in travel time correlate with better health outcomes. Our results are unambiguous: travel time to cities matters. This result is robust to controlling for a number of variables which may impinge on both transportation and child mortality, mainly economic development and population density, both of which are also measured at the sub-national level. Thus, our results should be interpreted as the correlation between transportation and child mortality above and beyond within-region, time-varying differences in economic development and population density; it is not simply the case that otherwise-occurring improvements in living standards, which are known to result in lower mortality, are picked up by our measure of travel times.

Having established a correlation between child mortality and travel times, we examine whether our results may be driven by selection bias, using Oster's (2019) δ method. We find that selection on observables would need to be implausibly large to explain away our results. Specifically, if we assume the model could explain as much as 90% of the variation in the data, selection on unobservables would need to be at least 11.9 times as large as selection on observables in order to render the coefficient of travel time statistically indistinguishable from zero. We view this as strong evidence against selection bias as an explanation for our results. Our instrumental variables approach, exploiting orthogonality conditions in the data, supports a causal interpretation of the results. Our heterogeneity analysis also sheds light on potential drivers of the relationship: we find that economically worst-off places, as well as those with better institutions, stand to benefit the most from improved transportation.

Our main contribution, relative to the existing literature is that, because we have measurements for child mortality and transportation infrastructure at two points in time for a large number of sub-national regions, we are able to rule out fine-grained spatial heterogeneity (via the use of sub-national region fixed effects). In contrast, previous papers (e.g. Kadobera et al 2012; Sarrasat et al. 2018; Oldenburg et al 2021; Okwaraji et al 2021) typically rely on cross-sectional analyses covering a single region at a single point in time. Rare exceptions are Karra et al (2017) and Shon (2024), who examine multiple sub-national regions across developing countries as sampled in the Demographic and Health Surveys, but do not consider information on *changes* in travel time at the same location across multiple time points. Quattrocchi et al (2020) do consider changes in travel times, but only study child mortality in rural Malawi, whereas we look at a broad cross-section of countries.

The remainder of this paper is structed as follows. Section 2 provides an overview of the existing literature. In Section 3, we introduce the data used in this paper. Section 4 presents our empirical approach and main results, while Section 5 subjects our results to a battery of sensitivity analyses. We explore potential heterogeneities in Section 6 and offer some concluding remarks in Section 7.

2 Related Literature

2.1 Background

An under-studied bottleneck that challenges the growth of the developing world is infrastructure, or the lack thereof. Infrastructure is a broad term that encompasses sewages, water ways, electricity, telecommunications, transportation and more (National Research Council, 1993). Guest (2005), in *The Shackled Continent: Africa's Past, Present and Future*, discusses several consequences of low-quality infrastructure. The low quality of roads causes people to receive less for what they sell and pay more for what they need to buy. These higher prices are caused by bad roads as it becomes more time consuming, difficult, and costly to get goods to markets. With the cost of manufactured goods so high, there are little resources left for people to spend on medicine and health services. Hence, where roads improve, income tends to rise (Guest, 2005). Better roads may not only increase income, but also make way for time reallocations. Guest (2005) mentions that a typical Ugandan woman carries a ten-liter water jug for over ten kilometers, every day. An increase in the availability of transportation infrastructure may therefore help increase accessibility to everyday needs such as nutrition and water. This will generate higher productivity which can be explained by time reallocation towards activities like work or education, and though the notion that a better fed population often causes productivity to rise (Bloom et al 2003)

Economic development and health are closely related. Using microeconomic estimates, Weil (2007) finds that health directly benefits economic development, albeit to a smaller extent than suggested by cross-country regressions. According to Bloom et al (2003) a healthier labour force is mentally and physically more robust, productive, energetic, and earn higher wages. Absence from work due to illness (of oneself or of a family member), is less likely to occur when workers are in good health. Illness has a negative effect on hourly wages especially in developing countries where higher proportions of the labour force are engaged in manual labour (Bloom, et. al, 2003). The World Bank (1993) observes additional effects of improved health and its contributions to economic growth, explicitly, increases in the enrolment of children in school, and the use of alternative recourses otherwise spent on treating illness.

2.2 Health and Transportation

Transportation infrastructure is the system of public works that are designed to facilitate movement. Transportation infrastructure is a crucial component of broader public infrastructure, which is thought to be key in improving economic and health outcomes. Litman (2012) argues that transportation infrastructure improvements can generate large health benefits which are often overlooked. Several reports like the United Nations (2005) and the Blair Commission (2005) have highlighted the importance of public investment with, at its core, infrastructure.

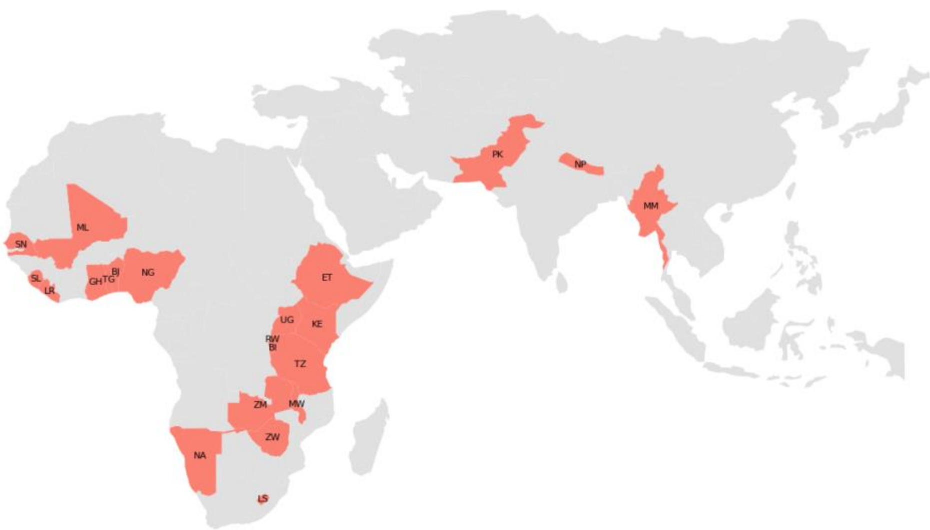
Moreover, Agénor (2008) suggests that the best strategy for enhancing the consumption, supply, and accessibility of health and healthcare services in the long run, and thus stimulating growth, might not be by increasing direct government spending on the healthcare sector, but rather increase spending on additional inputs, in this case infrastructure. A reason behind favoring increases in public spending on infrastructure is that infrastructure services can have a strong growth-promoting effect through increasing productivity and the rate of return on capital. This effect is particularly evident when the stock of infrastructure is low. Low-income countries thus find themselves at a substantial disadvantage.

As discussed in the introduction, several researchers have examined the health – transportation nexus. In a study of road improvements in Morocco, Levy (2004) employs both a pre-post design and a treatment analysis, where a treated group of farms and villages was compared to an untreated group. The improvement of the road network led to an increase in visits to health care clinics and facilities. Wagstaff and Cleason (2004), examining progress on the Millennium Development Indicators and building on Filmer and Pritchett (1999), find that improvements in the quality of the road infrastructure significantly reduced tuberculosis mortality, under-five mortality, and maternal mortality. In a cross-sectional analysis of 14 rural areas in Burkina Faso, Sarrassat et al (2018) find that shorter distances to care facilities are associated with more frequent use of such facilities, but detect only marginal impacts of distance on child mortality. In contrast, Kadobera et al (2012) find better survival outcomes for children living closer to care facilities in rural Tanzania. Even in developed country settings, distance to medical services has been shown to affect usage (see Lemont 2024 and Buchmueller et al 2008 for the United States; Clarke 1998 for Australia), which underscores the relevance of this paper.

To the best of our knowledge, no existing study considers *changes* in transportation infrastructure across multiple countries *and* time points. Thus, our contribution vis-à-vis of the existing literature is clear: we show, relying on *within-region* variation in transportation over time across 290 sub-national regions, that lower travel times correlate with lower child mortality. Our results are not attributable to unobserved heterogeneity, and survive a large battery of robustness checks.

3 Data

Our dataset covers 290 sub-national regions from 22 countries in Africa and Asia (see Appendix Table A1 for details). This section provides definitions and sources for the main variables used in this paper. Figure 1 provides a visual overview of the countries in the sample. Inclusion in the sample is determined by data availability: we included all countries for which sub-national child mortality data and travel time data were available from the respective sources, as detailed below.



Key	
BJ	Benin
BI	Burundi
ET	Ethiopia
GH	Ghana
KE	Kenya
LS	Lesotho
LR	Liberia
MW	Malawi
ML	Mali
MM	Myanmar
NA	Namibia
NP	Nepal
NG	Nigeria
PK	Pakistan
RW	Rwanda
SL	Sierra Leone
SN	Senegal
TZ	Tanzania
TG	Togo
UG	Uganda
ZM	Zambia
ZW	Zimbabwe
ZW	Zimbabwe

Figure 1. Countries included (in red) in Africa and Asia.

3.1 Dependent Variable: Child Mortality

Child mortality data come from the United Nations Inter-agency Group for Child Mortality Estimation (2021a, 2021b). Our variable of interest is the under-five child mortality rate, i.e. the number of deaths of children aged under the age of 5 per 1,000 live births. The IGME data provide this information at the first sub-national level (similar to U.S. states or European NUTS-1 regions) for some countries and at the second sub-national level (akin to U.S. counties / European NUTS-2 regions) for others. Here, we use data for the first sub-national, since some of the other variables we employ are only available at the first sub-national level. Appendix Figure A1 shows the distribution of sub-national mortality rates, grouped by country and year.

The IGME data are compiled from censuses, vital registration records, household surveys, including the Demographic and Health Survey, and other records (for details, see Alkema and New 2014). While the data are certainly not perfect, they have been shown to be accurate (Alkema et al. 2014), and are the best option available to researchers who study child mortality.

As an indicator of broader population health, the usefulness of child mortality has been forcefully advocated for by Filmer and Prichett (1999), who argue that child mortality is preferable to life expectancy, as data for the latter are statistically less reliable and more often the product of extrapolation. Filmer and Prichett (1999) also argue that child mortality, as an indicator, is preferred to infant mortality, as the latter is influenced by perinatal mortality. In sum, even though measuring child mortality is difficult, it is arguably the best option for the study of general health.

3.2 Independent Variable of Interest: Accessibility of cities

As a proxy for transportation infrastructure, travel time to the nearest city of at least 50,000 people is used as our independent variable of interest. For this variable, we combine data from two sources, both of which are collected via AidData's GeoQuery tool (Goodman et al. 2019).

For the year 2000, travel time data come from the European Union Joint Research Centre (2000). For a pair of locations on a raster grid, a cost-distance algorithm calculates the travel time using water- (navigable ocean, lake, or river) or land- (on/off roads) based travel, taking into account environmental factors (such as terrain ruggedness and land cover) as well as political factors (such as border crossings and protected areas). For a given sub-national region, the cost-distance algorithm determines the travel time to the nearest city of 50,000 or more inhabitants. For the sub-national region, the travel time variable is thus the travel time to the nearest city averaged across all cells that fall within the boundary of the sub-national region.

For the year 2015, travel time data come from Weiss et al (2018), and are the result of a collaboration between the Malaria Atlas Project, the European Union Joint Research Centre (who produced the travel time data for the year 2000) and other organizations including Google and the University of Twente. The methodology used was similar, and draws on roads data from Open Street Map and Google Maps. The main difference across the two datasets was the inclusion of minor roads, including "unpaved rural roads and exurban residential streets" (Weiss et al 2018, p. 334). The inclusion of minor roads is highly unlikely to affect travel time to large cities, since minor roads, by definition, are minor, and thus hardly contribute to any shortening of travel time. It is difficult to imagine a scenario where the inclusion of unpaved rural roads and exurban residential streets would shave off more than a few minutes of travel time to the nearest large city. This is dwarfed by the mean travel time of 247 minutes (4 hours and 7 minutes) in the data, such that the inclusion of minor roads is unlikely to affect our results. Appendix Figure A2 shows the distribution of travel times to cities at the sub-national level, grouped by country and year.

3.3 Control variables

In our empirical analysis, we control for a range of variables which may correlate with both travel times to cities and child mortality. These variables are measured at the sub-national level, thus allowing us to account for time-varying confounders defined on a fine geographic scale.

Economic development. First, we account for economic development by using data on nighttime light intensity as measured by satellites orbiting the Earth. In the absence of GDP data at the sub-national level, night lights are a well-established and validated proxy for economic development (Henderson et al. 2012, Chen and Nordhaus 2011). Economic development likely shapes (and is shaped by) the transportation infrastructure, and affects health outcomes through other channels; for example, Kammerlander and Schulze (2023) show that local economic growth reduces infant mortality. This motivates the importance of controlling for variation in economic development. Here, we use version 4 of the Defense Meteorological Satellite Program (DMSP) - Operational Linescan System (OLS) Nighttime Lights composites. Annual composites of the DMSP provide an average digital number (DN) corresponding to each 30-arc-second output pixel. The DN values range between 0-63, where higher numbers refer to greater brightness. Light from ephemeral occurrences such as gas flares and fires have been removed from the annual composites, as well as images for nights affected by sunlight, moonlight clouds, and other glare. The DMSP OLS data are only available until 2013; we therefore link data for the year 2013 to our travel time and child mortality data for 2015.

Population density. Rural areas may have both poor connectivity and poor health outcomes. Thus, it is important to control for population density, which allows us to rule out the possibility that the results we observe are confounded by differences in density.

Other variables. We also control for air pollution, forest cover, precipitation, temperature, and armed conflict, all measured at the sub-national level. Air pollution is proxied by the concentration of PM2.5 (particulate matter that is 2.5 micrometers in diameter, or smaller), which is well-known to affect health outcomes. Forest cover data are from the European Space Agency (Copernicus Climate Data Store, 2019), while precipitation and temperature data come from the long-running Climatic Research Unit Time Series dataset (CRUTS) hosted by the University of East Anglia (Harris et al 2020). Finally, armed conflict is operationalized with the number of deaths from conflict in a given sub-national region-year, and comes from the Uppsala Conflict Data Project (UCDP; Davies et al 2023). Summary statistics for all variables are shown in Table 1.

Table 1. Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
ln(Child Mortality)	580	4.5	.531	3.234	5.741
ln(Travel Time)	580	5.028	1.151	-2.373	8.228
ln(Conflict Deaths)	441	.98	1.853	0	10.4
ln(Night Lights)	580	7.707	2.32	0	14.469
ln(Air Pollution)	580	3.334	.505	2.378	4.889
ln(Temperature)	580	3.139	.216	1.812	3.401
ln(Pop. Density)	580	4.489	1.676	-1.22	9.299
ln(Forest Cover)	580	9.688	2.234	0	13.918
ln(Precipitation)	578	8.199	1.525	3.557	11.659

3.4 Descriptive Evidence

In Figure 2, we examine the relationship between child mortality and travel time to cities in a simple, unconditional binned scatter plot (Panel A) and in a conditional binned scatter plot (Panel B), which controls for all the variables we introduce in the previous sub-section (namely economic development, population density, air pollution, forest cover, precipitation, temperature, and conflict deaths). Both plots use all of the available variation (within as well as between sub-national regions).

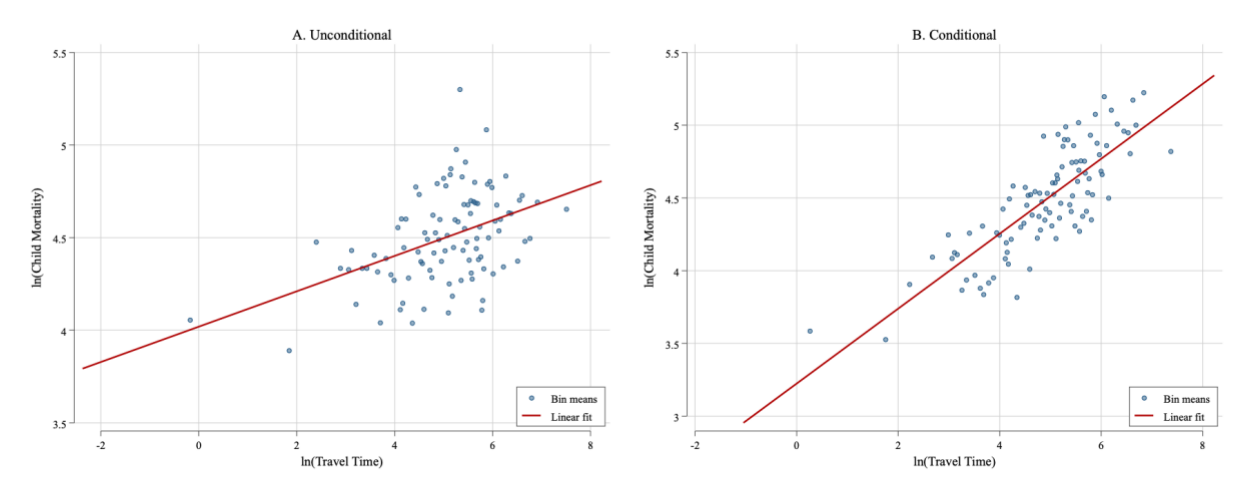


Figure 2. Travel time to the nearest city (> 50,000 people) and child mortality.
Notes. Binned scatter plots (100 bins).

The pattern which emerges from the data is stark. Regardless of whether one conditions on relevant controls, the correlation between longer travel times to cities (as one moves to the right of the graph) and higher child mortality is clearly apparent in the data. Of course, caution is in order: the relevant variation we are interested in occurs *within* regions over time. Figure 2 still may be confounded by unobserved between-region heterogeneity, but we do find *prima facie* indications that shorter travel times to cities are associated with better child survival rates.

4 Empirical Approach and Main Results

4.1 Empirical Approach

We estimate variants of the following specification:

$$\ln(Child\ Mortality\ Rate)_{it} = \beta_0 + \beta_1 \ln(Travel\ Time)_{it} + \mathbf{X}_{it}\gamma + \theta_i + \epsilon_{it} \quad (1)$$

where, for each sub-national region *i* measured at time *t*, *Child Mortality Rate* is the number of deaths of children under the age of 5, per 1,000 live births; *Travel Time* is the time, in minutes, necessary to reach the nearest city of 50,000 or more inhabitants, averaged across all cells in the sub-national region, $\mathbf{X}$ is a vector of control variables, θ_i us a set of sub-national region fixed effects, and ϵ is the error term.

The sub-national region fixed effects play a crucial role in this setting. A large number of variables that are likely to impinge on both infrastructure and health outcomes are likely at play, but do not vary over time within small spatial units. Location fundamentals, in particular (e.g. distance to the coast, malaria suitability), or the set of geographic features which can heavily shape a region's development trajectory, exhibit tremendous variation across regions, but can be adequately addressed with the use of fixed effects. We are thus able to isolate strictly *within*-region variation in travel times and child mortality, and examine the relationship between the two.

4.2 Main Results

Table 2 presents the main results of our analysis. In Column (1), we estimate a model without any independent variables except the sub-national region fixed effects. This model serves a benchmark for Column (2), where we find that longer travel times are associated with higher under-5 child mortality. Comparing the adjusted R^2 across the first two columns reveals that, in addition to being statistically significant, travel time also has sizable predictive power: the adjusted R^2 is just 0.21 in the benchmark model (Column (1)) but 0.63 in Column (2).

In Column (3), we control for changes in economic development at the sub-national level, as proxied by night lights. If the correlation we previously observed simply reflects improvements in economic development, rather than in transportation infrastructure *per se*, then omitting economic development from the specification would result in an upward bias. Empirically, controlling for night lights barely affects our previous estimates, such that we can comfortably rule out the possibility that economic development is driving the results.

In Column (4), we address the possibility that changes in transportation infrastructure may co-occur with changes in population density. Note that, in this setting, population density may suffer from the bad control problem: if higher density is a consequence of better transportation, as is often the case (see e.g. Hornung 2015 and Fenske et al 2023 for urban population growth in Prussia and early 20th century India, respectively), then controlling for population density mechanically reduces the coefficient of *Travel Time*. This is indeed what we observe in Column (4): the coefficient of *Travel Time* is now less than half of its uncontrolled size, but remains highly significant. Columns (5) – (9) introduce the other control variables sequentially, while Column (10) accounts for all covariates.[1]

[1] As an alternative to Table 2, we can also use analytic weights to assign different weights to different observations based on population density. This means that observations from more densely populated areas are given more influence in the estimation process. Analytic weights are defined such that the weight assigned to each observation is inversely proportional to its variance. Table A2 in the Appendix presents the corresponding results: the estimates remain statistically significant and quantitively large in all cases.

Table 2. Main results. Dependent variable: ln(Child mortality rate).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ln(Travel Time)		0.398***	0.345***	0.170***	0.354***	0.375***	0.413***	0.299***	0.404***	0.147***
		[0.025]	[0.025]	[0.060]	[0.026]	[0.030]	[0.022]	[0.026]	[0.024]	[0.056]
ln(Night Lights)			-0.136***							-0.067**
			[0.023]							[0.027]
ln(Pop. Density)				-0.849***						-0.652***
				[0.198]						[0.216]
ln(Conflict Deaths)					0.038***					0.005
					[0.012]					[0.012]
ln(Temperature)						-1.883				0.488
						[1.337]				[0.968]
ln(Precipitation)							-0.013			0.131
							[0.050]			[0.083]
ln(Air Pollution)								-1.293***		-0.689***
								[0.136]		[0.153]
ln(Forest Cover)									-0.168	-0.171**
									[0.139]	[0.078]
Sub-national FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	580	580	580	580	408	580	578	580	580	406
Adjusted R^2	0.211	0.628	0.666	0.736	0.641	0.631	0.640	0.714	0.630	0.763

Notes. All specifications include a constant term. Standard errors are clustered over sub-national regions. ***, **, and * denote significance at the 1, 5, and 10% respectively.

4.3 Quantitative Interpretation

What is the quantitative interpretation of our results? In Column (10), the coefficient of ln(*Travel Time*) is 0.147 ($p < 0.001$). Thus, a 1% increase in travel time to the nearest city of 50,000 or more inhabitants is associated with a 0.147% increase in the under-five mortality rate. The mean travel time in the sample is 247 minutes, while the mean mortality rate is 103.5 deaths per 1,000 live births. Our estimates thus imply that a 30-minute improvement (*decline*) in travel time results in 1.85 lives saved per 1,000 live births.

Stated differently, these numbers also imply that, conditional on crucial time-varying controls (including economic development and population density) and unobserved time-invariant heterogeneity (as captured by the fixed effects), a sub-national region one standard deviation above the mean travel time has a child mortality rate equal to 112.8 deaths per 1,000 live births. A 1 S.D. improvement in travel times thus saves 112.8 – 103.5 = 9.3 lives per 1,000 live births.

How many lives would be saved? Using country-level data on crude birth rates from the World Development Indicators (World Bank, 2016) and summing across all 22 countries in the sample, our estimates imply that, ceteris paribus, 275,061 lives would be saved *each year.* Thus, better transportation has the potential to, simply put, save lives.

Estimates of the statistical value of life, in developing country settings, are notoriously difficult to find, with Leon and Miguel (2017) providing a rare exception. They study the decisions made by travelers on their way to Freetown International Airport, in Sierra Leone, and how they decide between travel options with varying prices and risk levels (e.g. speedboats, hovercrafts, and ferries). Leon and Miguel (2017) report a statistical value of life equal to USD 577,000. Using their estimate at face value, saving 275,061 lives with an average statistical value of 577,000 amounts to $159 billion *per year* in lives saved, for a 1 S.D. reduction in travel time to the nearest city of 50,000 or more inhabitants. $159 billion is 4.4% of annual GDP for the 22 countries in the sample.

Under significantly more conservative assumptions, the quantitative importance of our results remains staggeringly large. Before we proceed with these more conservative assumptions, let us state unambiguously that the assumptions are in no way normative. We absolutely do not assert that the lives of poor people are less worthy of living or less statistically valuable. The objective of this exercise is to seek a lower bound for the magnitude of the welfare improvements that come hand-in-hand with travel time improvements, not to downgrade the lives of people in developing countries. With this in mind, let us resume our analysis. As Leon and Miguel (2017) point out, airport travellers are positively selected (in terms of income), relative to the broader population. To account for this selection, we can devise a more conservative estimate by assuming that (i) for simplicity, the within-country distribution of income is approximately normal; and (ii) airport travelers are drawn from the top quartile of the income distribution, while would-be saved individuals are in the bottom quartile. Under these assumptions, mean income in the top quartile is 2.47 times larger than income in the bottom quartile. We can then divide the Leon – Miguel estimate by 2.47 in order to approximate the statistical value of life for the poorest 25%, which yields $233,603. Under this conservative scenario, the total statistical value of lives saved is $64.3 billion. In turn, $64.3 billion is 1.8% of annual GDP for the 22 countries. These numbers are thus quantitatively highly meaningful, despite the conservative approach.[2]

5 Sensitivity Analysis

5.1 Specification Curve

In this section, we examine the sensitivity of our results to all potential permutations of the control variables. Our seven control variables may be combined in 128 distinct ways, as $C_7^0 + C_7^1 + C_7^2 + \cdots + C_7^7$ = 128. Since empirical results can be sensitive to the choice of controls, we report the full enumeration in Figure 3.

[2] Under the alternate assumption that income is log-normally distributed, the magnitude of the effects depends on the standard deviation of income. The median Gini coefficient for the countries in the sample is 0.377, from which the standard deviation can be obtained by solving $G = 2\Phi\left(\sigma/\sqrt{2}\right) - 1$ for σ, where Φ is the standard normal CDF. Doing so yields Φ = 0.7, which makes the ratio of incomes in top quartile relative to the bottom quartile equal to 2.6. An adjustment ratio of 2.6 yields a 1.7% gain of annual GDP from a 1 S.D. reduction in travel time, which is still staggeringly large.

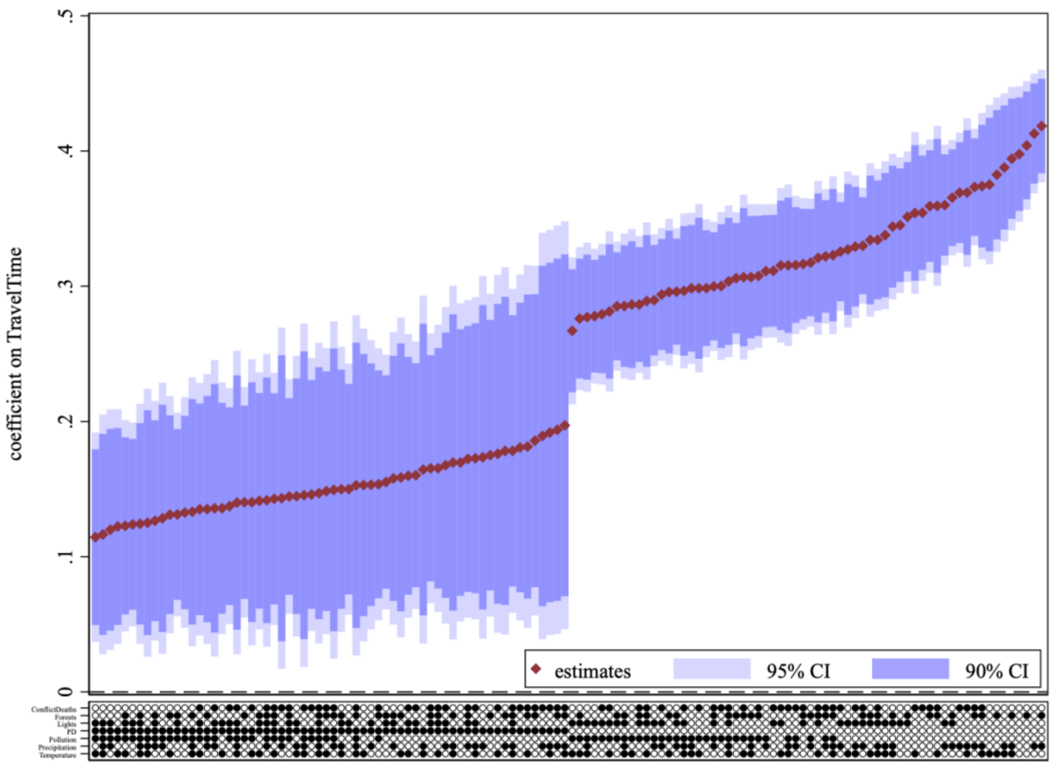


Figure 3. Specification curve for the coefficient of ln (Travel Time).
Notes. The bottom panel indicates which control variables are included in each specification. Estimates are sorted by size.

Figure 3 shows that, across all permutations, the positive correlation between shorter travel times and smaller child mortality is clearly visible. We do not find a single negative coefficient, or even a single one that is statistically indistinguishable from zero, which gives us confidence in our results. As was the case in Table 2, the inclusion of population density makes the point estimate of *Travel Time* noticeably smaller, but it nonetheless remains positive and meaningful.

5.2 Randomization Inference

In this section, we implement randomization inference, which allows us to estimate the p-value of the observed test statistic under the null hypothesis. The idea is to randomly permute the 'treatment' assignment (in this case, the value of *Travel Time*) and compute the test statistic for each randomization. The randomization inference p-value is then the proportion of randomizations that yield a test statistic at least as extreme as the observed test statistic. The advantage of randomization inference is that it does not rely on any assumptions about the distribution of the test statistic under the null hypothesis, but instead, relies on the randomization of the treatment assignment in order to generate a distribution of placebo coefficients under all possible treatment assignments.

In practice, the number of possible randomizations is too large to compute the exact p-value. Instead, we can approximate the p-value by drawing a large number of randomizations and computing the proportion of randomizations that yield a test statistic at least as extreme as the observed test statistic. We perform 1,000 such randomizations here. Figure 4 shows the results: the dashed line showing the actual coefficient from Table 2 Column (10)), is further to the right than the entire distribution of placebo coefficients, such that the randomization p-value is 0.00. This gives us reassurance that our travel time variable is indeed picking up a true association between transportation infrastructure and child mortality, rather than a spurious correlation.

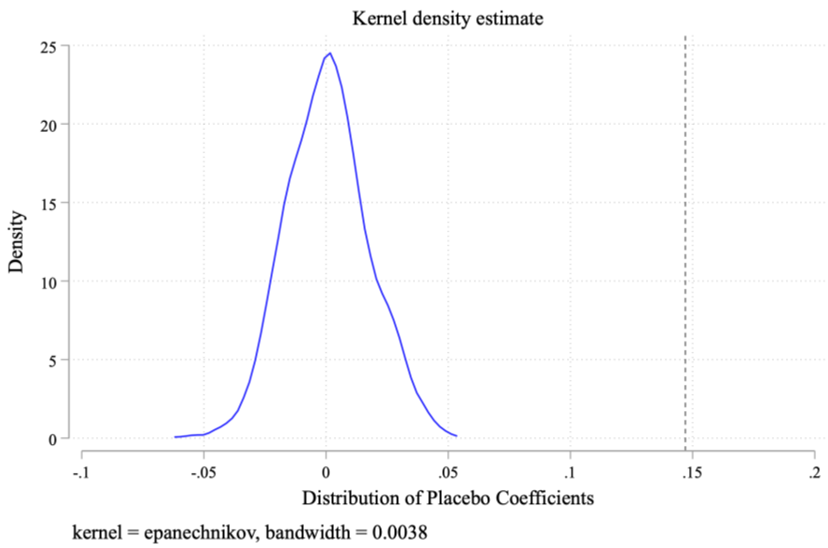


Figure 4. Randomization Inference. The dashed line is the observed effect from Table 2 Column (10).

5.3 Selection on Unobservables

The results we have documented so far may simply be the outcome of selection on unobservable characteristics. Ruling out such selection is therefore an important step towards understanding whether our results may have a causal interpretation. To do so, we rely on Oster’s (2019) δ method.

Stated simply, Oster's δ method answers the following question: how large would selection on unobservable characteristics have to be, relative to selection on observable characteristics, to make the coefficient of *Travel Time* statistically indistinguishable from zero? The coefficient of proportional selection, δ, is calculated by examining changes in the coefficient of the independent variable of interest as well as changes in the proportion of variation in the data explained by the model.

Since population density matters (Table 2), we include population density in the benchmark model. In the controlled model, we condition on all covariates from Table 2 (namely forest cover, conflict deaths, night lights, air pollution, precipitation, temperature, population density, and sub-national fixed effects). Figure 5 shows, for various R^2 values, how large selection on unobservables would need to be in order to explain away our results.

If we assume the model can explain 90% of the variation in the data, then, in order to make *Travel Time* insignificant, selection on unobservables would have to be at least 11.9 times as large as selection on all the variables we control for. This strikes us as implausible. Even if we assume that the model could explain *all* of the variation in the data, the degree of selection required to remove the observed correlation between child mortality and travel time would still have to be a very large 1.8 (or almost twice as much selection on unobserved characteristics as on observed characteristics). We interpret these findings as indicative that selection is extremely unlikely to be driving our results.

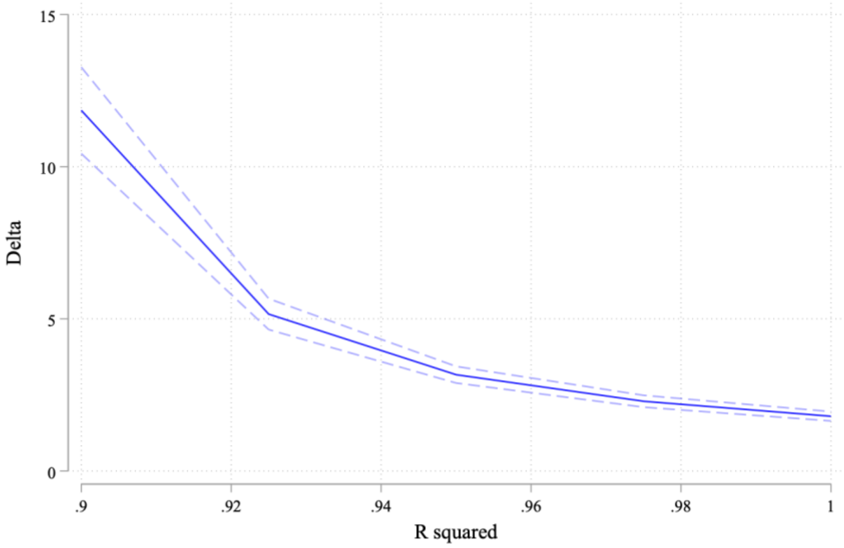


Figure 5. Estimates of Oster's (2019) δ.

Notes: Dashed lines represent the 95% CI of δ. Jackknife variance estimates for δ are obtained by excluding one country at a time.

5.4 Potential Outlier Regions

While the fixed effects estimates from Table 2 are positive and significant, we can open the black box and see whether the effect is driven by a small number of sub-national regions. For example, it may be the case that the within-region correlation is positive for some regions but negative for others; in such a case, the overall point estimate might mask the heterogeneity in the effect. We therefore run a regression of child mortality on travel time separately for each of the 290 sub-national regions in the sample. Since we have two data points per region, we have just enough information to estimate a region-specific slope. Note that we cannot quantify the uncertainty around these estimates, as doing so would require more data points. However, we can still use the estimates to ask whether the effect of travel time on child mortality might be negative in some regions and positive in others.

We find that such is not the case: just 8 out of 290 regions (2.76%) have a negative slope, while 97.24% have a positive slope. This suggests that the positive effect of travel time on child mortality is not driven by a small number of regions, but is instead a general pattern across the sample.

5.5 Instrumental Variables

An ideal instrumental variables approach would rely on an exogenous source of variation in transportation infrastructure which affects child mortality only through its effect on travel times, and not through any other direct or indirect channels. In the absence of such naturally occurring variation, and in the interest of establishing whether our results may have a causal interpretation, we implement Lewbel's (2012) heteroskedasticity-based instrumental variables approach. The idea behind this approach is to use the heteroskedasticity in the error term of the regression to identify the causal effect of the endogenous variable on the dependent variable. Lewbel's method builds instruments by multiplying the endogenous variable by the residuals from a regression of the endogenous variable on all other exogenous variables. The resulting instruments are orthogonal to the error term in the regression of interest, and can be used to estimate the effect of the endogenous variable on the dependent variable.

Table 3 displays the results. *Travel Time* remains positive, large, and statistically significant, with $p < 0.05$. The instrument set is sufficiently strong in terms of explanatory power, as the Kleibergen-Paap rk LM statistic is 12.2, which is above the rule-of-thumb critical value of 10. Hansen's J test also fails to reject the null hypothesis that the generated instruments are jointly valid ($p = 0.168$). While strictly random variation in the treatment variable is of course preferred for causal inference, the best feasible (we believe) approach we implement here does support a causal interpretation of our results.

Table 3. Lewbel (2012) instrumental variables results. Dependent variable: ln(Child Mortality).

	(1)
ln(Travel Time)	0.371**
	(0.178)
ln(Night Lights)	-0.059**
	(0.025)
ln(Pop. Density)	-0.248
	(0.337)
ln(Conflict Deaths)	0.004
	(0.013)
ln(Temperature)	2.865
	(2.065)
ln(Precipitation)	0.124
	(0.087)
ln(Air Pollution)	-0.451*
	(0.251)
ln(Forest Cover)	-0.256*
	(0.138)
Sub-national region FE	Yes
N	439
Hansen's *J* p-value	0.168
Kleibergen-Paap rk LM statistic	12.242

Notes. All specifications include a constant term. Standard errors are clustered over sub-national regions. ***, **, and * denote significance at the 1, 5, and 10% respectively.

6 Heterogeneity Analysis

So far, we have established that our results are not specification-dependent, not driven by selection bias, and may be causally interpreted. In this section, we ask under which circumstances may the effect of transportation infrastructure be larger. In this analysis, we therefore interact *ln(Travel Time)* with a set of variables on which the effect of transportation infrastructure may be contingent. The regression equation is:

$$\ln(Child\ Mortality\ Rate)_{it} = \alpha_0 + \sum_{q=1}^{5} \alpha_q \left[\ln(Travel\ Time)_{\mathrm{it}} * D_{q,it}\right] + \mathbf{X}_{\mathrm{it}}\tau + \theta_i + v_{it} \qquad (2)$$

where $D_{q,it}$ indexes the quintiles q of the variable of interest. Equation (2) thus allows the coefficient of *ln(Travel Time)* to vary depending on the specific quintile of the given covariate of interest, while controlling for all other covariates.

Figure 6 shows the results of this analysis. The pattern that emerges is that the positive effects of transportation infrastructure are larger where socio-economic conditions are most dire. Panels A and B, respectively, show that sub-national regions with the highest initial levels of child mortality (as measured in the year 2000) and the lowest levels of GDP per capita (as proxied by night lights) experience the largest benefits from transportation infrastructure. This is consistent with the idea that transportation infrastructure may be particularly important in connecting poor areas to health services.

Panels C, D, and E offer additional corroboration for this idea, using country-level variables. Where educational attainment (years of schooling; Institute for Health Metrics and Evaluation 2015) is lowest (Panel C), transportation offers the largest benefits. This is also true if we examine female education (Panel D), which we take a close look at, given that the development economics literature has shown that education can have gender-specific effects (see for example Heath and Jayachandran 2017). In turn, Panel E shows that the benefits of transportation infrastructure are largest where country-level government health spending (World Bank 2016) is lowest. To be clear, our results do not suggest that transportation infrastructure is a substitute for (other forms of) economic development and health spending. We simply find that the benefits of transportation infrastructure appear to be largest where socio-economic conditions are most dire, which should provide impetus for improving conditions in the most disadvantaged areas.

In addition to development-related variables, we also find some evidence that the effect of transportation infrastructure may be contingent on political-institutional factors. In Panel F, we interact *ln(Travel Time)* with the political corruption index from the Varieties of Democracy project (Coppedge et al 2024, Pemstein et al 2024). The effectiveness of transportation appears to rise with smaller degrees of corruption (larger values of the index). Similarly, the interaction between *ln(Travel Time)* and institutional quality (Kuncic 2014) in Panel G shows a modest uptick, suggesting that better institutions are more conducive to life-saving effects of transportation. Finally, in Panel H, we do not find evidence that improving transportation has diminishing returns, as the effect of *ln(Travel Time)* does not vary across quintiles of initial travel times (as measured in the year 2000).

It is important to note that, throughout this analysis, we do not focus on the main effects of the variables interacted with *ln(Travel Time)*. Instead, we focus on the interaction terms, which capture the extent to which the effect of transportation infrastructure may be contingent on these variables. Thus, our results cannot be interpreted as saying that, for example, education exerts a *negative* effect on child mortality; our analysis only suggests that transportation infrastructure is more effective at reducing child mortality where education is low.

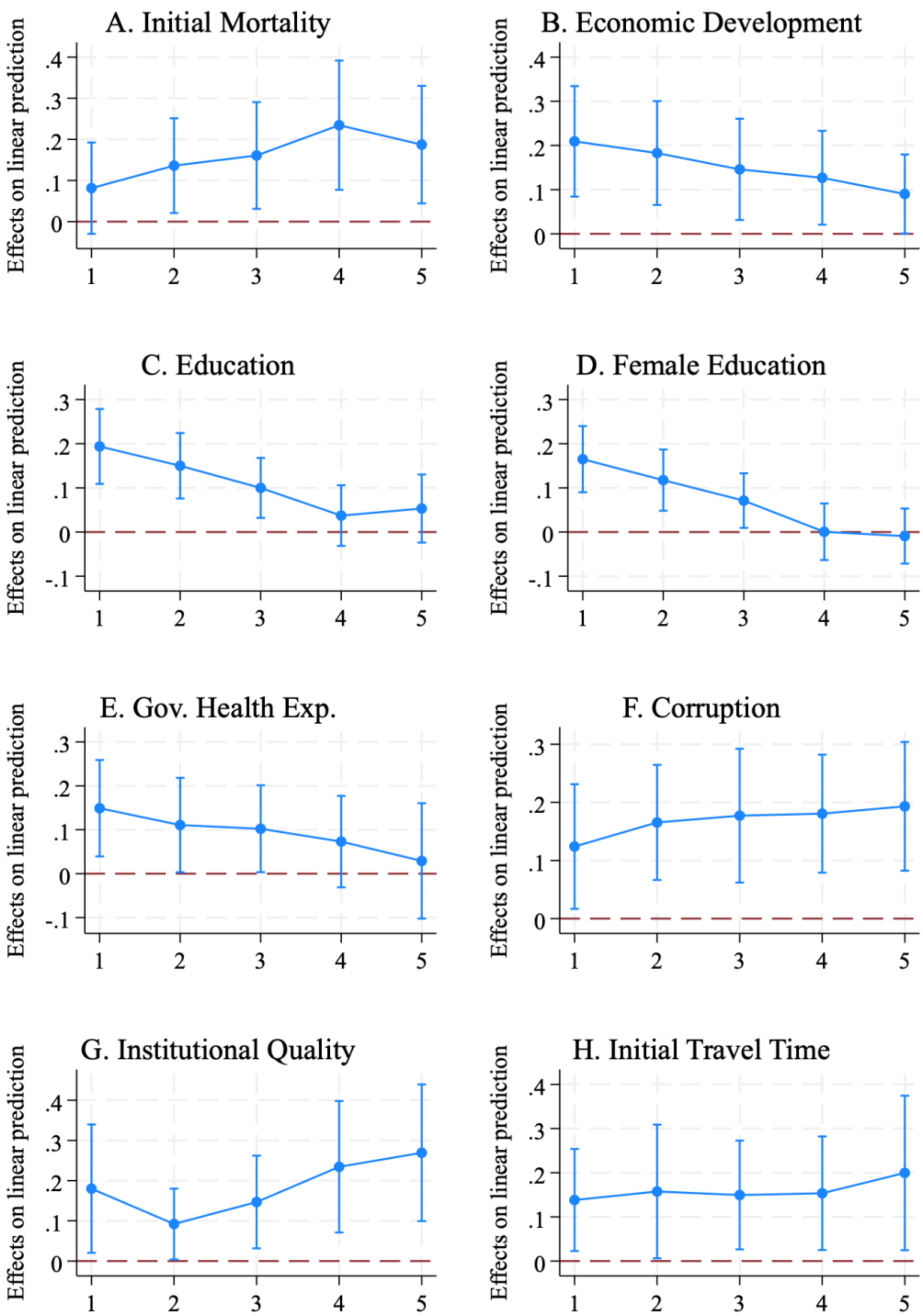


Figure 6. Potential Mechanisms.
Notes. Each sub-graph plots the coefficient of ln(Travel Time) at each quintile of the variable shown in the sub-graph title.

7 Concluding Remarks

In this paper, using data for 290 sub-national regions across 22 developing countries, we have studied the link between transportation infrastructure and health outcomes, within-sub-national regions over time. Specifically, transportation infrastructure was operationalized as travel time to the nearest city of 50,000 or more inhabitants, and health outcomes were operationalized as under-5 mortality rates.

We found that, even after conditioning on covariates and unobserved fine-grained heterogeneity (as accounted for by sub-national fixed effects), a 1 S.D. reduction in travel time translates to 9.3 fewer deaths per 1,000 live births, which is sizable. To understand just how sizable this effect is, consider that the average under-5 mortality rate in our sample is 103.5 deaths per 1,000 live births: a 1 S.D. reduction in travel time is thus associated with a 9% reduction in under-5 mortality rates. In turn, given the statistical value of life estimate from Leon and Miguel (2017), our results imply that a 1 S.D. reduction in travel times generates gains equivalent to 1.8 – 4.4% of GDP. This is a substantial effect, and it suggests that transportation infrastructure investments can have large effects on health outcomes in developing countries. Our results survive a large battery of robustness checks, are not driven by selection, and may be interpreted causally, as supported by our heteroskedasticity-based instrumental variables approach (Lewbel 2012). We also find some evidence of heterogeneous effects: reductions in travel time have a larger impact where poverty is most dire, and where institutions are more functional.

Our findings lend strong empirical support for more investments in transportation infrastructure, particularly in regions plagued by high rates of child mortality. Such investments are obviously useful in other ways, such as market access, but also appear to exert a more direct effect on health. The possibility of improving health through investment in transportation offers some hope for policy-makers and public health officials seeking to achieve sustainable improvements in health outcomes.

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Transportation infrastructure and child mortality: Sub-national evidence for 22 developing countries

Appendix – For online publication only

Table A1. List of countries and sub-national regions

Country	Abbr.	Sub-national regions
Benin	BEN	Alibori, Ouémé, Plateau, Zou, Atakora, Atlantique, Borgou, Collines, Donga, Kouffo, Littoral, Mono
Burundi	BDI	Bubanza, Kirundo, Makamba, Muramvya, Muyinga, Mwaro, Ngozi, Rutana, Ruyigi, Bujumbura Mairie, Bujumbura Rural, Bururi, Cankuzo, Cibitoke, Gitega, Karuzi, Kayanza
Ethiopia	ETH	Southern Nations, Nationalities and Peoples, Tigray, Afar, Amhara, Benshangul-Gumaz, Dire Dawa, Gambela Peoples, Harari People, Oromia, Somali
Ghana	GHA	Ashanti, Western, Brong Ahafo, Central, Eastern, Greater Accra, Northern, Upper East, Upper West, Volta
Kenya	KEN	Baringo, Kajiado, Kakamega, Kericho, Kiambu, Kilifi, Kirinyaga, Kisii, Kisumu, Kitui, Kwale, Bomet, Laikipia, Lamu, Machakos, Makueni, Mandera, Marsabit, Meru, Migori, Mombasa, Murang'a, Bungoma, Nairobi, Nakuru, Nandi, Narok, Nyamira, Nyandarua, Nyeri, Samburu, Siaya, Taita Taveta, Busia, Tana River, Tharaka-Nithi, Trans Nzoia, Turkana, Uasin Gishu, Vihiga, Wajir, West Pokot, Elgeyo-Marakwet, Embu, Garissa, Homa Bay, Isiolo
Lesotho	LSO	Berea, Thaba-Tseka, Butha-Buthe, Leribe, Mafeteng, Maseru, Mohale's Hoek, Mokhotlong, Qacha's Nek, Quthing
Liberia	LBR	Bomi, Maryland, Montserrado, Nimba, River Cess, River Gee, Sinoe, Bong, Gbapolu , Grand Cape Mount, Grand Bassa, Grand Gedeh, Grand Kru, Lofa, Margibi
Malawi	MWI	Northern, Central, Southern
Mali	MLI	Bamako, Gao, Kayes, Kidal, Koulikoro, Mopti, Ségou, Sikasso, Timbuktu
Myanmar	MMR	Ayeyarwady, Naypyitaw, Rakhine, Sagaing, Shan, Tanintharyi, Yangon, Bago, Chin, Kachin, Kayah, Kayin, Magway, Mandalay, Mon
Namibia	NAM	Oshana, Oshikoto, Otjozondjupa, Zambezi, Erongo, Hardap, Kavango, Khomas, Kunene, Ohangwena, Omaheke, Omusati, !Karas
Nepal	NPL	Province 1, Province 2, Bagmati, Gandaki, Province 5, Karnali, Sudurpashchim
Nigeria	NGA	Abia, Delta, Ebonyi, Edo, Ekiti, Enugu, Abuja, Gombe, Imo, Jigawa, Kaduna, Adamawa, Kano, Katsina, Kebbi, Kogi, Kwara, Lagos, Nassarawa, Niger, Ogun, Ondo, Akwa , Ibom, Osun, Oyo, Plateau, Rivers, Sokoto, Taraba, Yobe, Zamfara, Anambra, Bauchi, Bayelsa, Benue, Borno, Cross River
Pakistan	PAK	Baluchistan, Federally Administered Tribal Areas, Federal Capital Territory, Khyber Pakhtunkhwa, Punjab, Sindh
Rwanda	RWA	Kigali, Eastern Province, Western Province, Central Province, Northern Province
Senegal	SEN	Dakar, Saint-Louis, Sédhiou, Tambacounda, Thiès, Ziguinchor, Diourbel, Fatick, Kaffrine, Kaolack, Kédougou, Kolda, Louga, Matam
Sierra Leone	SLE	Eastern Province, Northern Province, Southern Province, Western Area,
Tanzania	TZA	Arusha, Lindi, Manyara, Mara, Mbeya, Morogoro, Mtwara, Mwanza, Njombe, Pemba North, Pemba South, Dar es Salaam, Pwani, Rukwa, Ruvuma, Shinyanga, Simiyu, Singida, Tabora, Tanga, Zanzibar North, Zanzibar South and Central, Dodoma, Zanzibar West, Geita, Iringa, Kagera, Katavi, Kigoma, Kilimanjaro
Togo	TGO	Centrale, Kara, Maritime, Plateaux, Savanes
Uganda	UGA	Central, Eastern, Northern, Western
Zambia	ZMB	Central, Western, Copperbelt, Eastern, Luapula, Lusaka, Muchinga, North, Western, Northern, Southern
Zimbabwe	ZWE	Bulawayo, Midlands, Harare, Manicaland, Mashonaland Central, Mashonaland East, Mashonaland West, Masvingo, Matabeleland North, Matabeleland South

Table A2. Replication of main results with population density as analytic weight. Dependent variable: ln(Child mortality rate).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ln(Travel Time)		0.190***	0.179***	0.099***	0.188***	0.169***	0.267***	0.168***	0.205***	0.194***
		[0.047]	[0.043]	[0.024]	[0.047]	[0.053]	[0.035]	[0.031]	[0.067]	[0.057]
ln(Night Lights)			-0.193***							-0.101**
			[0.055]							[0.043]
ln(Pop. Density)				-0.676***						-0.489***
				[0.145]						[0.173]
ln(Conflict Deaths)					0.029*					-0.014
					[0.015]					[0.018]
ln(Temperature)						-3.729				0.380
						[2.359]				[2.451]
ln(Precipitation)							0.145			0.245
							[0.139]			[0.197]
ln(Air Pollution)								-0.960***		-0.117
								[0.279]		[0.210]
ln(Forest Cover)									-0.085	-0.225***
									[0.108]	[0.063]
Sub-national FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	580	580	580	580	408	580	578	580	580	406
Adjusted R2	0.154	0.596	0.642	0.714	0.597	0.605	0.698	0.668	0.599	0.772

Notes. All specifications include a constant term. Standard errors are clustered over sub-national regions. ***, **, and * denote significance at the 1, 5, and 10% respectively.

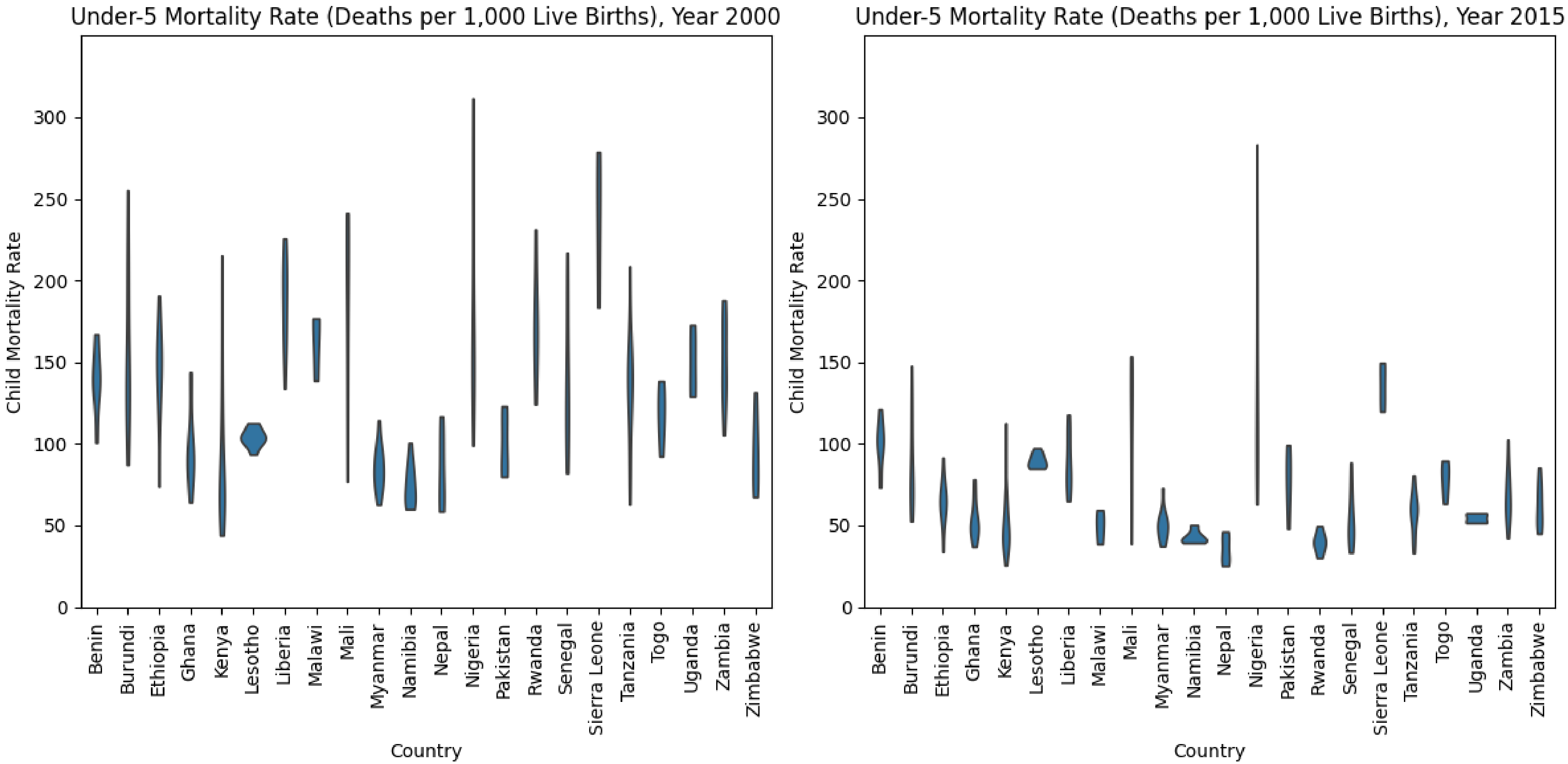

Figure A1. Distribution of child mortality rates by country and year.

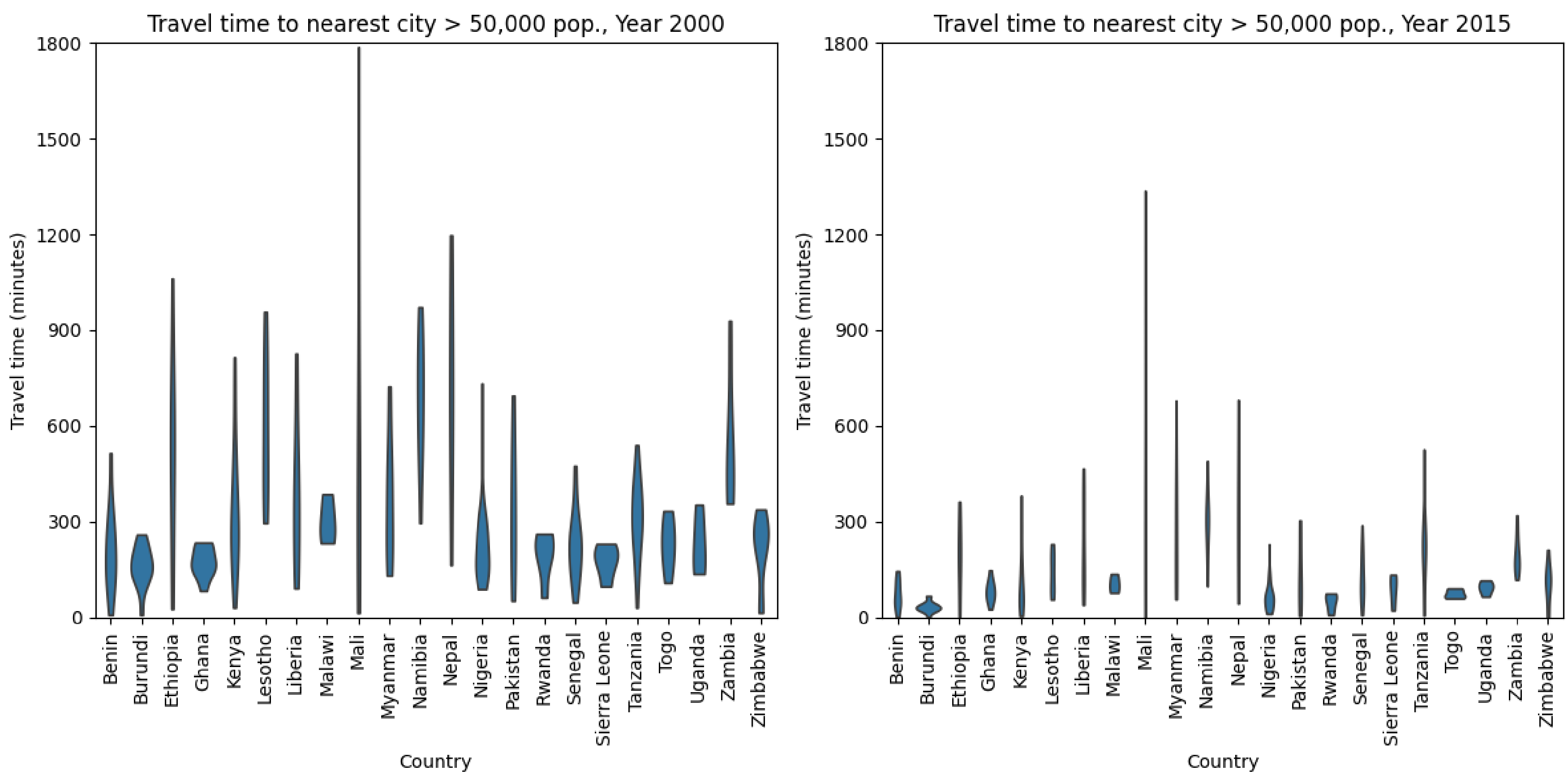

Figure A2. Distribution of travel times by country and year.

Note: For readability, we exclude the sub-national region of Timbuktu (Mali) from this graph, which saw a large increase in travel time.