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Conducting Fiscal Incidence Analysis for Sustainability: The Case of Government Infrastructure Spending

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Abstract

Who benefits from government fiscal policies? Providing an answer to this question is a crucial element in maintaining the sustainability of government policies. In this paper we extend traditional tax incidence studies to benefit incidence studies, focusing especially on the incidence of government-provided public goods in the form of urban transportation infrastructure spending. We develop a new approach to benefit incidence studies—a “time-savings approach”—that allows us both to measure individual access to government infrastructure programs and to estimate the time savings to individual households from these infrastructure programs. We then apply this time-savings approach in two detailed applications, using micro-level and geo-spatial data from Indonesia and Mozambique. We find that the time-savings approach has the potential to provide estimates at the household level of the monetary value of government urban infrastructure improvements via the value of reduced travel time, illustrating the power of this approach in allocating and valuing the benefits of public goods like transportation infrastructure spending for individual households. Fully realizing the potential of the time-savings approach requires access to data with accurate time and distance variables at the household level.

Keywords: infrastructure; sustainability; tax and benefit incidence analysis; fiscal incidence analysis; public goods; geo-spatial data

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1. Introduction

The ways in which government fiscal policies—taxes and expenditures—affect the distribution of income have long been a central focus of public economics. The study of these distributional effects falls under the rubric of “fiscal incidence analysis”. Traditionally, the effects of taxes via “tax incidence” have been far more studied than the effects of government expenditures (e.g., “expenditure incidence” or “benefit incidence”). However, it is the combined impact both of tax incidence and expenditure incidence that is of most interest in answering the basic question of “Who benefits from government fiscal policies?”. Providing an answer to the distributional effects of government programs is a

crucial element in maintaining the sustainability of government policies. Policies whose benefits are widely distributed are more likely to generate sustainable political support. In contrast, policies that are seen as benefitting mainly either higher-income individuals or individuals who are politically well-connected are less likely to maintain similar support. Regardless of this, providing an answer requires conducting fiscal incidence analysis.

The theory of tax incidence is quite developed, with a huge—and still growing—theoretical and empirical literature that attempts to answer the question “Who bears the tax burden?” Benefit incidence is far less advanced, in large part because it has been much more difficult to develop a comprehensive theory of benefit incidence and also because it has been much more difficult to identify at the individual level who benefits from many types of government expenditures and how they value these expenditures. These difficulties make it very challenging to quantify “Who receives the benefits of government expenditures?”. In particular, as discussed in more detail later, research on the incidence of one important aspect of government expenditures, or government infrastructure spending, is extremely limited due mainly to its inability to value and to allocate the benefits of infrastructure investments to individuals. Our primary goal here is to advance such analyses.

The extension of benefit incidence to government infrastructure spending is complicated by the challenge of attributing infrastructure benefits to individuals or households, which is not as straightforward as in the case of allocating tax burdens to households or allocating the benefits of government spending on cash or in-kind transfers, public health, or education to households. A common approach in benefit incidence studies is to measure the incidence using various indicators of access of households to government expenditure programs (the “access indicators approach”), such as access to the nearest hospital, pharmacy, clinic, school, water supply, or market. While useful, the access indicators approach often does not allow the actual value of individual access stemming from these expenditure programs to be estimated and allocated to individual households. As an alternative approach, we develop a method that, with appropriate data, has the potential for allocating and valuing the complex multidimensional nature of transportation infrastructure investments to individual households. We call this approach the “time-savings approach” because it relies upon data—and assumptions—that allow us both to measure individual access to government infrastructure programs and to estimate the time savings to individuals from these infrastructure programs. This approach therefore has the potential for us to estimate the value to individual households of these transportation infrastructure programs via the time savings of these programs and to allocate these time savings to individual households. Fully realizing this potential requires access to data that allow matching time and distance variables to individual households and their incomes, data that we do not at present have.

We illustrate the practical application of these two approaches using micro-level and geo-spatial data from Indonesia and Mozambique. The access indicators approach allows us to analyze the distribution of various infrastructure access indicators (e.g., ease of access to the nearest hospital, pharmacy, clinic, or school), highlighting the importance of using granular infrastructure access indicators for investigating the distributional impacts of road infrastructure investments. The time-savings approach allows us to monetize the time-savings benefits of infrastructure projects and to assign these benefits to individual households.

We find that both approaches provide much useful information on the differential benefits across households of infrastructure programs, highlighting the importance in benefit incidence studies of considering variation in access to healthcare facilities and educational institutions, and of identifying the resulting variations in time savings from this differential access. Importantly, we also find that the time-savings approach has the

potential to provide estimates at the household level of the monetary value of road infrastructure improvements, illustrating the potential of this approach in valuing and allocating the benefits of transportation infrastructure to individual households.

In the next sections we briefly discuss the basics of a tax incidence study (TIS) and also those of a simple benefit incidence study (BIS), emphasizing the difficulties of valuing and allocating the benefits of these expenditure programs to individual households. We then focus upon government infrastructure programs, where we discuss the standard “access indicators approach” used to examine the distribution of benefits of these programs, and we also develop a “time-savings approach” based on geo-spatial data for allocating and valuing these benefits. In the following two sections we illustrate the application of these approaches using data for Indonesia and then for Mozambique. We also discuss the “next steps” needed to apply fully our approaches to a benefit incidence study. The final section summarizes and concludes.

2. How Do Fiscal Policies Affect the Distribution of Income? Tax Incidence Studies and Benefit Incidence Studies

2.1. Tax Incidence Studies (TISs)

There is an enormous literature on tax incidence, most of which builds upon the analysis of [1]. See especially [2] for a detailed discussion of the methods of tax incidence analysis, including its many challenges. For comprehensive surveys, see [3–5]. For examples of applied work, see [6,7] and, again, [2]. For a recent, specific analyses of the distributional effects of taxes in developed and developing countries, see [8–11].

The basic elements of a tax incidence study (TIS) are straightforward. Start with the pre-tax/pre-transfer income of household unit h (or I_h), define government tax instrument i (or T_i , with each tax specified in real monetary units as the total amount of taxes collected from the program), and introduce “allocators” of program i to household unit h as s_{ih} , which specify the share of program i borne by unit h . Then the post-tax income of unit h (or Y_h) is simply:

$$Y_h = I_h - \sum_i s_{ih} T_i,$$

where the term $[\sum_i s_{ih} T_i]$ represents the total amount of taxes borne by unit h . From this calculation, one can further calculate such useful measures as effective tax rates, pre- versus post-tax income distribution, Gini coefficients of the resulting income distributions, Suits indices of any or all of the tax instruments, and the like. All of these calculations attempt to answer the key question of tax incidence: *Who pays the taxes (or gets the transfers)?*

The basic elements of a TIS are therefore straightforward:

1. Define and specify the income of the household unit using household survey data.
2. Determine the allocators for each tax instrument using the theory of tax incidence.
3. Calculate the resulting tax burden by household unit.

In practice, of course, there are many additional questions and issues that must be addressed, as discussed in detail by [2].

2.2. Benefit Incidence Studies (BISs) and Their Complications

Almost all governments spend for several basic (economic) reasons: to redistribute income, to provide for “public goods” (e.g., national defense), to correct for “externalities” (e.g., pollution), or to provide social insurance (e.g., health insurance). See, for example, [12–14]. So the resulting government expenditures can be broadly classified as:

- Cash transfers, including social insurance programs;

- Publicly provided private goods, or goods that are provided by government but that are also available in the private sector (including in-kind transfers such as education and health);
- Public goods (and mixed public goods and externalities), or goods that are either non-rival or non-exclusive or both.

(Note that governments also spend for macroeconomic stabilization reasons, and political considerations of course may also drive spending decisions.) How do these government expenditures affect the distribution of income? This is the subject of a benefit incidence study (BIS), but it remains an often investigated even if a still somewhat unresolved issue.

There are many examples of studies that attempt to determine the incidence of all government expenditure programs, often in combination with the incidence of all government taxes. Classic studies largely began with pioneering work for the U.S. by [15], followed by [16–19], many others since these early studies. The analysis of fiscal incidence in developing countries has also expanded over the years, following initial important contributions by [20,21] and driven in large part by the World Bank and the International Monetary Fund (IMF).

However, determining the incidence of government expenditure programs in a benefit incidence study can be challenging, considerably more difficult than a standard tax incidence study. Valuing and allocating the benefits of cash transfers are relatively straightforward tasks—these methods are essentially the same as those used in a TIS methodology in treating a cash transfer as a negative tax valued by its cash magnitude and borne fully by the recipient. Valuing and allocating the benefits of publicly provided private goods and in-kind transfers are harder but still manageable, following the basic methods of a TIS.

For example, a simple benefit incidence study (BIS) of cash or in-kind transfers starts with pre-tax/pre-transfer income of unit h (I_h), a government in-kind expenditure program j (or G_j , with each program specified in real monetary units as the total expenditures on the program), and the “allocators” of program j to unit h , or s_{jh} (or the share of program j that benefits unit h). Then the post-program income of unit h (Y_h) is:

$$Y_h = I_h + \sum_j s_{jh} G_j,$$

where the term $[\sum_j s_{jh} G_j]$ represents the total amount of benefits received by h , which can be denoted simply as B_h . Similar to the tax/transfer incidence approach, this benefit incidence study answers the question: *Who receives the benefits of government expenditures?*

The basic steps in a BIS are therefore straightforward, broadly similar to those of a TIS:

1. Calculate spending per recipient/beneficiary of the government expenditure program using overall budget data and recipient/beneficiary data.
2. Using household survey data, estimate the distribution of recipients/beneficiaries by the relevant population group (e.g., by income, gender, ethnicity, geographic location, and so on).
3. Allocate the public spending that accrues to each relevant population group for the government expenditure program (and calculate measures of each group's benefit from the government expenditure program—by income, gender, ethnicity, geographic location, and so on).

This basic BIS methodology has been usefully developed and applied in many contexts, as will be discussed later.

However, although valuing and allocating the benefits of cash or in-kind transfers are relatively straightforward, there are new complications that arise when extending the basic BIS methodology to other types of government expenditure programs beyond these simple transfers. Indeed, valuing and allocating the benefits of government-provided public goods, including infrastructure spending in its many forms (including urban

transportation infrastructure expenditures), are enormously challenging and indeed remain unsettled, as we discuss next.

These difficulties presented by public goods (and their many variants) are twofold. *First, it is hard to measure the output (and so the true value) of these programs. Second, it is hard to allocate (or assign) the benefits of these programs to individual recipients.* Both of these difficulties are complex, demanding, and unresolved.

To be sure, these two issues are present in the case of tax incidence studies in at least some forms. However, with a TIS, it is simply assumed that the amount of tax revenue generated by a tax accurately measures the true “burden” of the tax; the presence of an “excess burden” (or a “deadweight loss”) from the tax is almost always ignored on the implicit assumption that the magnitude of the excess burden/deadweight loss is relatively small and so of secondary importance. Also, in the case of a TIS, the theory of tax incidence allows the burden of the tax to be linked directly to the individual(s) who bears the burden, and this individual(s) can usually be identified with appropriate data; the same considerations apply to a BIS of an in-kind or cash program. However, in the case of a benefit incidence study, especially of a public good, neither of these conditions—the amount of the benefit from government spending and the identification of those individuals who benefit from the program—is clear-cut, unambiguous, or resolved.

The classic studies noted earlier that estimated the distribution of all government expenditures (and all taxes)—[15–19] and many others—simply assumed that the value of government spending on public goods was measured by the (average) cost to the government of providing the relevant public good and that the benefit to individual households was allocated by various measures, such as in proportion to the number of household members (i.e., per capita), to household income, to household wealth, to household consumption, or to taxes paid. These studies used standard methods for estimating the distributional effects of taxes and non-public good categories of expenditures. These assumptions allowed the valuation of the various categories of public good expenditures and their allocation to individual households to be easily made. See also [22,23], both of whom developed and applied methods to value specific categories of government expenditures via estimates of the individual willingness to pay for these categories. This approach is not practical in most settings, given its extensive data requirements. These assumptions are clearly incorrect, or at least incomplete, but they have the virtue of allowing one to value and to allocate the benefits of these government programs. More recent studies attempt to identify specific users, and some also attempt to estimate individual willingness to pay for government expenditures, but data issues often make these attempts quite difficult. As a result, the problems of valuation and allocation of a public good remain vexing in a BIS. For pioneering benefit incidence studies, see [24–28]. For useful reviews of the methods and limitations of the BIS methodology, see [20,29–31].

So there are many questions and issues that must be answered and resolved for benefit incidence studies. Some of these questions are similar to issues that arise in tax incidence studies, such as those relating to the unit of observation, the measurement and the calculation of income, the time frame for the analysis, the values of the allocators, and the potential effects of reranking and path dependency. However, there are even more difficult questions for benefit incidence studies, almost all of which arise because, again, it is difficult to measure the output (and so the true value) of government expenditure programs and also because it is difficult to allocate the benefits of many government programs to individual recipients.

To illustrate this, remember the basic steps in a BIS. Especially in step 1 (or estimating unit costs per recipient and identifying users), there are many complicating factors for public goods:

- Do we include capital as well as recurrent spending on the service?

- How do we incorporate administrative spending?
- How is cost recovery treated?
- Where do we get data on service use—from official administrative data, household surveys, or other sources (e.g., field experiments)?
- Should we take into account regional and other variations in unit costs?
- How do we deal with biases in the data arising from self-reporting?
- How do we match data sources (e.g., information in the household survey does not always match public expenditure data)?
- How do we aggregate users into groups?
- Should the effects of government spending (especially construction and other similar capital projects) on the income of construction workers (including multiplier effects) be considered as a benefit?
- Should the indirect effects of government spending (again, construction and capital projects) on product prices (e.g., water and sanitation) and so on worker productivity be considered as a benefit?

For example, cost measures are often used to value the government program, and these cost measures may not be a good measure of the true benefits of the government program. Some studies estimate the value of a public service by the difference between the total current cost to produce the service and the amount people have to pay to consume the service, a method first used by [20,21]. Cost measures usually reflect current costs and not long-term capital costs: a BIS is mainly an exercise in current accounting because it measures current flows of benefits and not these flows over time. Unit cost measures may not capture inefficiencies in public provision, they may not capture quality differences between (say) urban and rural areas, and they may not be available for some types of government programs. Participation/utilization rates for beneficiaries may not be available, and self-reported participation/utilization rates may be biased. Only average benefits are measured, not marginal benefits of incremental changes in government programs. Also, direct benefits may be identified, but indirect benefits are not captured, so that some important impacts on social welfare are not considered. Relatedly, interactions with the private sector (e.g., “crowding out”) are not captured or even considered, and the mechanisms by which distribution occurs are not identified because the underlying “framework” is unspecified. The basic approach is a static and partial equilibrium approach with no individual behavioral adjustments allowed. Dynamic/behavioral/general equilibrium/macroeconomic responses are not captured; the dynamic intertemporal effects may be especially important. Finally, as with a TIS, the “true” counterfactual—What would be the distribution of income in the absence of government programs?—can never be known for a BIS.

Underlying all of these complicating factors are the two basic problems of how do we measure the benefits of government spending (e.g., by the amount of the spending, by the willingness to pay for the service, and so on) and how do we allocate these benefits to recipients (especially for public goods) (e.g., rich/poor household, male/female-headed household, size of household, occupation of household members, location of household, and so on)? There are no obvious or easy answers to these questions.

As a result, benefit incidence studies remain enormously challenging, and the studies that have been performed—and there are many—exhibit some significant limitations, as well-documented in the surveys by [30–32]. Indeed, in another survey, van de Walle (1998) has said that benefit incidence studies are still in their “infancy”, and this remains true even today [29].

What these many issues imply is that the BIS approach cannot easily be applied to government programs for which private beneficiaries cannot be readily identified or for

which valuations (even via unit cost data) are not readily available. These government expenditure programs include many important categories of public goods, such as:

- Communicable disease prevention;
- Public order and safety;
- The judiciary;
- Public awareness programs (e.g., family planning);
- Cultural programs;
- Environmental protection;
- National defense.

Included here is basic infrastructure, like roads, railroads, electricity and power generation, water facilities, sanitation and sewerage facilities, health facilities, and schools.

2.3. The Special Case of Government Infrastructure Investments

The difficulties of valuing and allocating the benefits of public goods apply to all types of public goods. However, at least in the case of government infrastructure investments, there are opportunities for their valuation and allocation, largely because many types of infrastructure investments generate benefits to individuals via channels that largely revolve around reducing the time that individuals spend traveling to government facilities like education, health, culture, and recreation services. If we can first measure the reduction in individual travel time attributable to infrastructure investments and then place a monetary value on the time reduction for these individuals, we can then conduct a detailed, micro-level benefit incidence study of these infrastructure investments. This basic approach—a “time-savings approach”—is not readily available for most other types of public goods, especially public order and safety, the judiciary, public awareness programs, environmental protection, and national defense. Given the importance of infrastructure investments in the spending of many governments, there is much potential for conducting a BIS for at least this one central component of government spending on public goods, even if other components of public goods spending remain a challenge.

In the next two sections, we first provide a detailed framework that establishes the foundation for a BIS that extends fiscal analysis to government infrastructure spending via a “time-savings approach”; we also discuss the basic elements of the more traditional “access indicators approach”. We then illustrate both approaches in a modified BIS framework with two specific applications to ongoing infrastructure projects, one in Indonesia and another in Mozambique. For more recent applications that use alternative methods for valuing transportation infrastructure, see [33,34]. Also, see [35,36] for somewhat broader perspectives on valuation that relate especially to sustainability issues.

3. Adding Government Infrastructure Spending to Benefit Incidence Studies

3.1. The Standard BIS Approach to Infrastructure Spending: The “Access Indicators Approach”

How might the BIS approach be modified to measure the distributional effects of basic infrastructure investments? One commonly used approach—the “access indicators approach”—mainly relies upon measuring how infrastructure investments affect individual household or firm access to such indicators as the nearest hospital, pharmacy, clinic, school, water supply, or market. Often these access indicators are simple binary indicators denoting whether an individual has any access to the facility (a value of 1) or whether they have no access at all (a value of 0). Sometimes additional information is available on the extent of access (e.g., the number of individual visits to a facility, the amounts of individual expenditures on the relevant service of the facility). These indicators are also

sometimes available only at the aggregate level for specific geographic locations (e.g., by urban versus rural areas, by regions, by provinces, and the like).

Recall that valuing and allocating the benefits of infrastructure requires addressing two basic challenges: one must measure the output (and so the true value) of these programs, and one must allocate (or assign) the benefits of these programs to individual recipients. Recall also each of the three steps in the BIS approach and consider how these steps might be modified to analyze the distributional effects of various types of infrastructure spending.

The first step in the BIS approach was: *Calculate spending per recipient/beneficiary of the government expenditure program using overall budget data and recipient/beneficiary data.* Household budget and other household survey data should be available, and beneficiaries should be able to be identified using these data, depending on the type of infrastructure investment. For example, for roads one can use household expenditures on gasoline together with geographic location; for power generation, one can use household expenditures on electricity; for water improvements, one can use expenditures on water; and so on. Household survey data also usually have information on such demographic variables as the number of household members, the age of household members, their gender, their incomes, and their geographic location.

The second step in the BIS method was: *Using household survey data, estimate the distribution of recipients/beneficiaries by the relevant population group.* For infrastructure investments, geographic location is especially crucial.

The third step was: *Allocate the public spending that accrues to each relevant population group for the government expenditure program and use standard measures to represent the distributional effects.* At this point, the calculation is largely a mechanical one.

Note that the specific application of these steps in the access indicators approach depends on the specific type of access indicator that is available. These data often come from household surveys. If the only access indicator is a 0–1 binary variable, then these steps mainly allow beneficiaries to be identified; that is, does an individual have some measure of access to, say, the nearest water supply (or the nearest hospital, pharmacy, clinic, school, or market)? Even with only a 0–1 binary variable of access, these steps may also allow some monetized value of this access to be allocated to the household, a value typically based on an estimate of government spending on the relevant service. With more detailed access indicator measures, say, household expenditures on public water services, it is possible to assign to the household a monetary value of, say, government investments in the construction of new water supply services.

Even so, the assumptions necessary to make these calculations are subject to some debate. One can of course always use the monetary amount of the expenditure (or some other commonly used valuation method), as many previous studies have done, and this assumption is useful as a first approximation. One can also allocate the monetary amount to individual households by various methods (e.g., equal per capita amounts, amounts in proportion to household consumption, income, wealth, or taxes). However, these assumptions are clearly incorrect or at least incomplete. Note also that geo-spatial data can be used to measure access, although it is only recently that geo-spatial data have been used and most prior studies have relied mainly on household survey data.

There are many examples of these methods as applied to public expenditures on education and health; although somewhat dated, see the many country studies cited in [29–31,37,38]. Examples of the incidence of infrastructure spending (mainly water and sanitation) are far more limited and include but are not limited to:

- Colombia [20]: Water and sanitation infrastructure, allocated by household payments.

- Malaysia [21]: Water and sanitation infrastructure, allocated by household in proportion to household income.
- Colombia [39]: Water and sanitation infrastructure, allocated by household payments.
- Tanzania [40]: Water and sanitation infrastructure, allocated by household payments and by region (urban versus rural).
- The Philippines [41]: Water and sanitation infrastructure, allocated by region and by household in proportion to household income and also in proportion to household members.

These studies found quite varied distributional impacts. For example, ref. [20] first identified the factors in Colombia that determined the probability that a household has water and sanitation services available and (conditional upon having the services available) the probability that the household uses the services. He then examined the amount of new investments in these services over several years in the early 1970s. He found that new investments in water and sanitation in Colombia had a strong pro-poor (or progressive) impact, especially for households in large cities. Note that [20] also examined the incidence of other categories of government expenditures, along with conducting a full tax incidence study. Ref. [21] also conducted a complete benefit and tax incidence analysis for Malaysia. Similarly, ref. [41] used regional government expenditure data to examine the incidence of water and sanitation infrastructure spending in the Philippines, assuming that the benefits from spending in any region are distributed equally per household across the region. Because water and sanitation spending tend to be concentrated in poorer regions, the incidence of these infrastructure expenditures is strongly pro-poor. However, an alternative assumption that allocated the spending to households in proportion to their income share generated a distributionally neutral pattern of benefit incidence. The results for Tanzania in [21] also demonstrate the crucial role of incidence assumptions. In the absence of detailed information on the use of water and sanitation services, ref. [21] simply assumed that spending was distributed in proportion to income. Not surprisingly, ref. [21] found that the distribution of water and sanitation spending was very pro-rich and so quite regressive. Further, an updated study of Colombia by [39] found that public expenditures on water and sanitation services in Colombia were poorly targeted, so that much of the government subsidies for water and sanitation services went to middle- and upper-income groups. Finally, ref. [40] estimated for Tanzania that the poorest quintile received about one tenth of the subsidies to water services, while the richest quintile received about two fifths of the subsidies. These varying results demonstrate the sensitivity of the results to specific allocation assumptions, as well as to specific country circumstances.

More recently, ref. [42] estimated the impact of various types of public infrastructure (e.g., piped water, piped gas, sewage, garbage collection, and phone lines) on owner-occupied housing values in Brazil using a different technique based upon hedonic pricing methods. He argues that the imputed prices of the various types of public infrastructure, as reflected in the price of owner-occupied housing, are able to provide estimates of the values of access to public infrastructure at the household level, at least for those households who own their own homes. His results indicate that including the imputed values of access to these public services for owner-occupied homeowners has a significant and progressive impact on the distribution of income. The clear implication of these results is that differential access to public infrastructure has important effects on the distribution of income, at least as measured by the impact of public infrastructure access on house values of homeowners. Extending these results to renters is in principle possible but heavily dependent on whether comparable housing characteristics are available for renters. See also

[43] for a discussion and analysis of approaches to measuring the benefits of public education.

Note that, aside from Soares [42], most country studies do not include infrastructure investments other than water and sanitation. There are few country studies that attempt a benefit incidence study of transportation infrastructure investments, including road projects. Even so, there are in fact numerous studies of the economic impacts of transportation infrastructure programs in developed and developing countries, especially for railroad infrastructure investments. However, many of these studies have mainly focused on aggregate outcomes (e.g., economic growth, productivity, employment, and prices). These studies go back to classic work on U.S. railroads by [44,45], who found that differences in freight rates benefited some areas in the U.S. relative to others, without having much impact on aggregate levels of income or on economic growth. More recent studies have found that expanding access to railroads in the U.S. often—but not always—had significant economic impacts. For example, ref. [46–48] all find that transportation infrastructure spending had large effects on the economic growth and trade patterns of regions and cities in the U.S. [49] estimate that rail access had a large positive effect on urbanization in mid-western cities of the U.S. in the pre-Civil War era. Ref. [50] apply a reduced-form expression derived from general equilibrium trade theory to estimate the impact on U.S. railroad expansion from 1870 to 1890 on agricultural land prices, and they find that access to markets had significant impacts on county agricultural land values.

There are also numerous studies in developing countries that demonstrate the impacts of railroad and road infrastructure spending on aggregate outcomes like: employment in rural areas of Peru [51]; short- and long-term economic growth in China [52]; per capita income levels across sectors in China [53], including urban–rural wage differentials [54]; the productivity of formal versus informal firms in rural India [55]; agricultural outcomes (e.g., employment, output, income, and wealth) in rural India [56]; city population growth, especially via rural–urban migration, in sub-Saharan Africa [57]; local economic activity (e.g., employment, wages, days worked, and number of micro-enterprises) in rural India [58]; and access to healthcare in Arab towns in Israel [59].

Increasingly, there are studies especially for developing countries that examine the effects of transportation infrastructure spending on less aggregate economic variables, especially rural poverty. For example, see: [60] for China; [61] for Papua New Guinea; [62] for Tanzania; [63] for Vietnam; [64] for Kenya; [65] for Ethiopia; [66] for Madagascar; [67] for Bangladesh; [68] for Bangladesh and Ethiopia; [69] for South Africa; [70] for Cameroon; and [71] for China.

Of most relevance for our work, several recent studies use geo-spatial data to examine the effects of road construction in developing countries on the access of individuals and firms to markets and other economic indicators. Ref. [72] combined geo-spatial data on road improvements in Ethiopia with establishment-level data on manufacturing firms to estimate the impact of a reduction in input tariffs on firm productivity. They found that a reduction in tariffs leads to a larger increase in firm productivity in areas where better roads improve access to other intranational markets, so that road infrastructure reinforces trade liberalization. Ref. [73] also combined firm-level data for informal firms in the manufacturing sector with geo-spatial data from the Ethiopian Road Sector Development Programme in order to measure improvements in road infrastructure and their impacts on the size and composition of the formal and informal sectors in Ethiopia. Their geo-spatial data describe the incremental improvements in road surface and travel time needed to cross each road segment and thereby allowed them to calculate the impact of the road enhancements on the average travel time needed to cross each segment of road. They found that improvements in road connectivity have positive effects on productivity and wages in the formal sector, even while having the opposite effects for informal firms.

Overall, most—although not all—of these studies find that improved access to roads and related infrastructure has positive effects on households via such channels as lower travel time costs for accessing public services (e.g., education, health, and social services), lower prices for these services, a higher marginal product for their labor, and the like.

However, despite the important contributions of these studies, there remain difficult and unresolved questions on how to quantify many of these effects of transportation infrastructure investments, especially on how to quantify these effects at the household level for a typical benefit incidence study. Even beyond the issues that we have already identified, ref. [74] identify several additional challenges in understanding the distributional impacts of infrastructure investments.

First, there are serious limitations in terms of data availability on transport habits, costs, and access, especially in developing countries. Indeed, access to infrastructure is related not only to travel time but also to the cost of transport, which can represent a major access barrier for low-income groups, as also noted by [75]. Ref. [74] define different dimensions of transport poverty based on a thorough review of the literature and on different definitions used by others. Transport poverty can affect individuals differently within a household. For example, female transport poverty may be different than male transport poverty [76]. Furthermore, the linkage of transport poverty to access to essential goods and services depends greatly on social, temporal, and geographical contexts, making it challenging to define transport poverty in a unique way. According to [74], transport poverty can exist along several dimensions, such as affordability, mobility (such as lack of access to motorized transport), and access (e.g., the difficulty of accessing social services). Some studies have shown that the poorest groups may not equally benefit from new or improved transport infrastructure and services, either due to lack of access to motorized transport or inability to afford transport services [63,67].

Second, ref. [74] emphasize that transport poverty—and transport inequality—is highly specific to geography and location. Measuring transport poverty requires using geo-spatial data, and integrating geo-spatial data into research is not always feasible.

Third, ref. [74] note that collecting transport data on costs and time can be very resource-intensive; however, if this data collection is included as part of national household surveys, there is potential to gather rich infrastructure access data.

All these challenges contribute to the difficulties of conducting a BIS for transportation infrastructure spending. Indeed, showing that infrastructure investment is progressive may not be very useful in assessing the distribution of benefits of this investment if the poor lack access to motorized transport or if they cannot afford it. These considerations suggest that transport poverty should be measured as a whole across the three dimensions of accessibility, affordability, and mobility, as emphasized by [74].

Even so, we believe that BIS analyses that focus on some components are useful as well. In the next section, we present an alternative method to the access indicators approach for valuing and allocating the benefits of road- and public transport-related infrastructure spending, in which we specify the channels through which infrastructure is likely to operate and the methods by which their effects can be allocated and valued at the individual household level. We call this approach the “time-savings approach” for BISs, as we discuss next.

3.2. Valuing and Allocating the Benefits from Transport Infrastructure Spending: A “Time-Savings Approach” for BIS Analysis of Transportation Infrastructure Spending

Investments in transport infrastructure may affect the welfare of individuals via several channels, all of which capture effects on the prices and costs of goods and services purchased and provided by individuals and on their own productivity, and all of which emerge from the previous literature on transportation infrastructure spending.

First, infrastructure investments may reduce the cost of accessing health, education, and other social services, which may lead to more (or more frequent) investments in human capital, such as education, health, culture, and recreation services.

Second, as a result of investments in infrastructure, individuals may experience a higher marginal product of *paid* labor supplied to the labor market (e.g., their wages) that also increases the marginal product of *unpaid* labor supplied to the household, such as in providing household members with basic necessities such as food, water, shelter, care for dependents, and the like, as well as in providing household members with non-necessities that increase the individual and collective utilities of household members via sports, culture, recreation, trips/travel, and such.

Third, individuals, as consumers, may experience lower prices for goods and services that use transport as a production input; that is, better road infrastructure can reduce prices of consumer goods and services and goods and services used as inputs by farmers and other producers.

These three channels are described in more detail below. In order to bring infrastructure spending into a fiscal incidence framework in which benefits of government infrastructure programs are first valued appropriately and then allocated to individual beneficiaries or payers, we evaluate each of these channels to determine whether each lends itself to a BIS.

There may well be additional possible channels, which we do not discuss in detail. For example, transport infrastructure may lead to higher marginal products of paid labor and paid capital (including land) because more units can be produced and sold with the same total amount of labor and/or capital; that is, individuals may experience a higher marginal product of labor with respect to paid labor supply, and individuals with capital assets may experience a higher marginal product of capital (including on their land), especially individuals in their role as agricultural producers who receive higher farm-related prices due to improved transport infrastructure. Quantifying these effects would require identifying:

- Which individuals are employed in the sectors that benefit the most from transport infrastructure;
- Which individuals own capital employed in the productive sectors that benefit the most;
- Which individuals own land in areas where the firms benefitting the most are located;
- Whether labor will see higher real wages, whether capital (including land) will see a higher real rate of return, or whether consumer prices will experience a real decrease.

These are all challenging tasks, especially using household survey data. We do not believe that estimates for these channels are possible at present, but we also believe that it is worthwhile to pursue efforts to measure and allocate benefits to agricultural producers from improved infrastructure and connectivity to markets in agricultural areas, provided the relevant agricultural landholder/agricultural producer information exists in either a main or a secondary survey. Also, an additional channel may work through risk reduction. Infrastructure planning that replaces or renews infrastructure losses from climate-related events, natural disasters, or other forms of accelerated depreciation reduces risks of certain individuals experiencing a permanent productivity loss from such catastrophic events. This risk reduction is likely most valuable for lower-income individuals, not because the loss of productivity is likely to be greater for them but because they are far more often living in areas likely to experience such catastrophes. At present, it is not obvious how this risk reduction can be systematically examined.

Consider now the three main channels in some detail.

Channel 1: Reductions in the cost of accessing public services (e.g., childcare, education, and healthcare). The demand for education responds to distance and school quality

[77]; that is, transport infrastructure may reduce travel times and therefore effective distance. Transport infrastructure may also indirectly increase school quality via decreased costs of accessing curricular and extracurricular goods and services, such as youth sports or trips to museums.

Also, the demand for health responds to distance. For example, see [63,64,67–69,78] for research that demonstrates this linkage in a wide range of countries. Transport infrastructure may reduce travel times and therefore effective distance, which may also reduce overall access costs for potential patients. Transport infrastructure may also indirectly increase health provider facility quality when medicines, medical supplies, and other inputs for healthcare service providers receive reduced prices via improved infrastructure.

Finally, more efficient transport may encourage more investments in childcare outside the home. Ref. [79] find that investment in such childcare increases the marginal product of labor for unpaid labor supplied within the household, which leaves childcare providers (typically women) with more time for leisure for the same amount of paid and unpaid labor, or with more time for paid labor supply for the same amount of leisure, or with more time for a greater labor share of skilled (either unpaid or paid) labor tasks.

The challenging tasks here are, again, quantifying or valuing these benefits and identifying the recipients (and allocating these benefits to the recipients). Both tasks are possible. *Allocating time savings to individuals making human capital investments via public social services could be done with existing microdata together with parameterization of the impact of transport infrastructure spending on travel time reduction.*

Channel 2: Increases in the marginal product of unpaid household labor. Improved transport infrastructure may reduce the total time of water collection from exterior taps or wells (for a fixed level of demand with exterior taps or wells), even though demand for water likely responds to increased water supply and a lower effective price of collection.

Also, as noted earlier, ref. [79] show that investment in childcare increases the marginal product of unpaid household labor, which affects such things as leisure time, unpaid (household) labor time, and paid labor time. Ref. [80] show that 0.6 percent of GDP investment in childcare reduces families' costs by as much as 50 percent, again leaving more time for leisure, for unpaid labor supply, or for paid labor supply.

How can these productivity effects be quantified? *Allocating infrastructure benefits to individuals via the household production channel could be done with existing microdata together with parameterization of the impact of transport infrastructure spending on travel time reduction and input cost reduction.*

Channel 3: Decreases in consumer prices due to decreases in input costs. Assuming that the domestic cargo transport sector is competitive and that there are at least some consumer goods-producing sectors that are also competitive, better transport infrastructure may reduce consumer prices via lower input prices of cargo transport/logistics.

Allocating benefits from a reduction in consumer prices to individuals by treating better transport infrastructure as a subsidy to transport-using sectors that is then passed on to consumers could be done with existing microdata together with parameterization of the impact of transport infrastructure spending on producer input costs. Incorporating this parameter into a standard "cost push" model (solved with an I/O matrix describing input intensities in the economy's production sectors) could then lead to a straightforward system of simultaneous equations, which could be solved to generate the reduction in consumer prices in those sectors assumed to be competitive.

Overall, then, valuing the benefits of transportation infrastructure expenditures and then allocating these benefits to individuals via Channels 1, 2, and 3 must start by measuring the effects of infrastructure spending on access and travel time to the relevant public facilities.

The applications that we discuss in the next two sections indicate how one can proceed. One application is for Indonesia; a second is for Mozambique. Both applications demonstrate how access to public facilities and estimated travel time to public facilities can be identified at the household level using survey data and geo-location data. In both cases, we explore the distribution of existing access indicators and travel times across income deciles. We present most of our results in figures, mainly for ease of presentation and understanding. All results are available upon request. Note that in these analyses we rank households by their income before any taxes or transfers, which we term “Pre-Fiscal Income”. The starting point is the calculation of “Market Income,” which comprises the sum of pre-tax wages, salaries, income earned from capital assets (rent, interest, or dividends), and private transfers. A complication is the treatment of contributory pensions, which can either be defined assuming that old-age contributory pensions are deferred income (PDI) or government transfers (PGT). Under the PDI scenario, Pre-Fiscal Income then equals Market Income plus contributory old-age pensions and minus the contributions to old-age pensions; under the PGT scenario, Pre-Fiscal Income equals Market Income; contributory pensions are included with the rest of the cash transfers, and the contributions are treated as a direct tax. We have also used income after taxes and transfers, or “Consumable Income”. We present mainly the results for Pre-Fiscal Income, mostly because the distribution of access does not noticeably vary when households are ranked by Consumable Income. All results are available upon request.

4. Application 1: The Distributional Effects of Road Infrastructure Investments in Indonesia

In this section we analyze the distributional effects of roads and public transport investments in Indonesia for households, as ranked by Pre-Fiscal Income. We use data for Indonesia based upon the national household survey from Survei Sosial Ekonomi Nasional (SUSENAS) for 2021 and the Potensi Desa (PODES) also for 2021 to match village- and district-level household income and infrastructure access characteristics; both the SUSENAS and the PODES surveys are nationally representative surveys, although PODES is primarily a rural or village-level survey. See [81] for further discussion of these surveys. The infrastructure access indicators used in the Indonesian surveys are: distance to the nearest school, clinic or hospital; ease of accessing the nearest school, clinic or hospital; and availability of public transport and road surface type.

For a recent important example of valuing road infrastructure in Indonesia that uses somewhat different methods than the ones we use here, see [82].

4.1. Data

As noted, we use PODES 2021 survey data along with SUSENAS income data to match village- and district-level income and infrastructure access characteristics, especially for access to health and education facilities. PODES provides rich information on various infrastructure indicators at the village level, while SUSENAS is the national socioeconomic survey conducted by Badan Pusat Statistik (BPS) Indonesia. PODES (Potensi Desa) is a dataset that provides information about the villages across the country. It was first collected in 2014 by the Ministry of Villages, Development of Disadvantaged Regions, and Transmigration, and it has been updated periodically since then. The dataset contains information about the socioeconomic characteristics of Indonesian villages, such as demographics, education, health, and economic activity. It also includes information about village infrastructure, such as roads, bridges, and irrigation systems. SUSENAS (Survei Sosial Ekonomi Nasional) is a national socioeconomic survey conducted by the Badan Pusat Statistik (BPS) of Indonesia. The main objective of SUSENAS is to collect data on

household income, consumption patterns, and other socioeconomic indicators in Indonesia. The survey collects data on a wide range of variables, including household demographics, education, health, labor force participation, and housing conditions.

4.2. Methods

We first identify infrastructure information available in PODES by translating the PODES questionnaire into English and identifying variable codes that capture infrastructure access information. We use Google Translate to translate the PODES 2021 questionnaire. We then merge district-level income data from SUSENAS with the village-level infrastructure indicators in PODES by aggregating up from the village to the district level, such that the dataset of interest is at the district level. Our final merged dataset is nationally representative, consisting of 34 provinces and 252,285 households. We use our merged dataset to rank households using Pre-Fiscal Income and Consumable Income to assess the distribution of access indicators.

4.3. Results: Distribution of Income

We first explore the distribution of Pre-Fiscal Income, Consumable Income, and poverty indicators across provinces. Note that we calculate the Pre-Fiscal Income Gini index for Indonesia to be 0.37 and the Gini index for Consumable Income to be 0.364. Figure 1a presents the distribution of Pre-Fiscal Income and Consumable Income and shows that the fiscal system is not particularly equalizing. Note that the red dotted line indicates the average village-level income in Indonesia as calculated from PODES 2021 survey data, which demonstrates the low income in villages relative to the rest of Indonesia. Relatedly, Figure 1b shows that low- and middle-income deciles are more concentrated in rural than in urban areas. In fact, headcount poverty in rural areas is almost twice as high as in urban areas, with an overall headcount poverty of 15 percent.

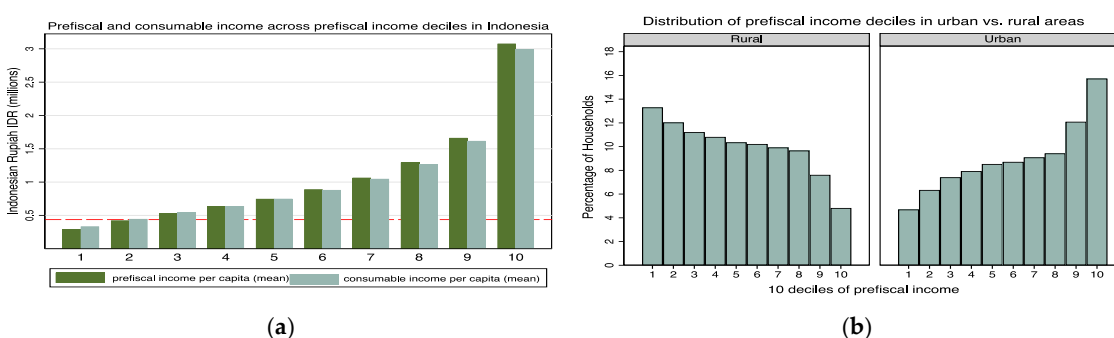


Figure 1. Distribution of income in Indonesia: Pre-Fiscal Income versus Consumable Income and Pre-Fiscal Income by urban/rural location. Source: Authors' calculations.

The literature on transport poverty defines “accessibility” as the ability to access key services or destinations, such as employment, education, health, or recreation, as shown by [83]. According to the Social Exclusion Unit as defined by [84], “accessibility poverty” is defined as the inability to reach key social or economic activities at a reasonable time, ease, and cost. Ref. [74] explain that accessibility poverty is inextricably linked to distributional inequality in the housing market, such that low-income households are often situated at urban peripheries with limited access to services. Furthermore, the lack of transport, long distances, and lack of connectivity in rural areas disproportionately affects low-income individuals because they are less likely to own motorized transport [85,86].

4.4. Results: Access Indicators Approach

Several recent papers have discussed the importance of using accessibility indicators to measure transport poverty and inequality. Some of them have used accessibility indicators to calculate transport poverty [74,87,88]. Recall that [74] define “transport poverty” as a disadvantage along three dimensions: accessibility, affordability, and mobility. They argue that “accessibility” is the most useful measure in assessing transport poverty. Ref. [74] also define “affordability” as the dimension that considers how difficult it is to meet transport costs, and it is measured by actual transport expenditures as a share of income. In addition, they define “mobility” as the dimension that considers how difficult it is to move from location to location due to a systemic lack of transport and mobility options, and they measure it by the lack of mobility services or infrastructure [74]. Given data limitations, we can only measure one aspect of transport poverty, or transport accessibility.

We now use these data to examine various measures of access to public facilities. First, as is commonly found around the world, we find significant differences in distance to school between urban and rural areas. As shown in Figure 2a, mean distances to the nearest primary school are almost double for rural areas compared to urban areas, and mean distances to high schools are longer than distances to primary and secondary schools; similarly, mean distances to the nearest clinics are greater for rural areas than for urban areas (Figure 2b). Within various distance categories, we observe that only about 20 percent of households can access a hospital within 5 kms, and almost 50 percent of rural residents face travel distances longer than 30 kms, a significant barrier to access. In large part, these differences are due to the availability—or lack of availability—of access to public transport (Figure 3). The obvious result of these differences in access is that it takes almost twice as long to travel to the closest clinic or hospital in rural versus urban areas (Figure 4).

Figure 5a shows that distance to the nearest schools is negatively but weakly correlated with Pre-Fiscal Income of the household. Mean distances to reach the nearest primary school are the shortest, followed by distances to reach secondary and high schools, which means that high schools are located further away than primary and secondary schools. Additionally, distances in rural areas are more than double those in urban areas. In Figure 5b, we see a “U-shaped” association of distance and Pre-Fiscal Income for rural households. In contrast, for urban households the relationship between Pre-Fiscal Income and mean distance to schools indicates that distance to schools largely falls as income increases across deciles, suggesting a negative correlation between distance to schools and income.

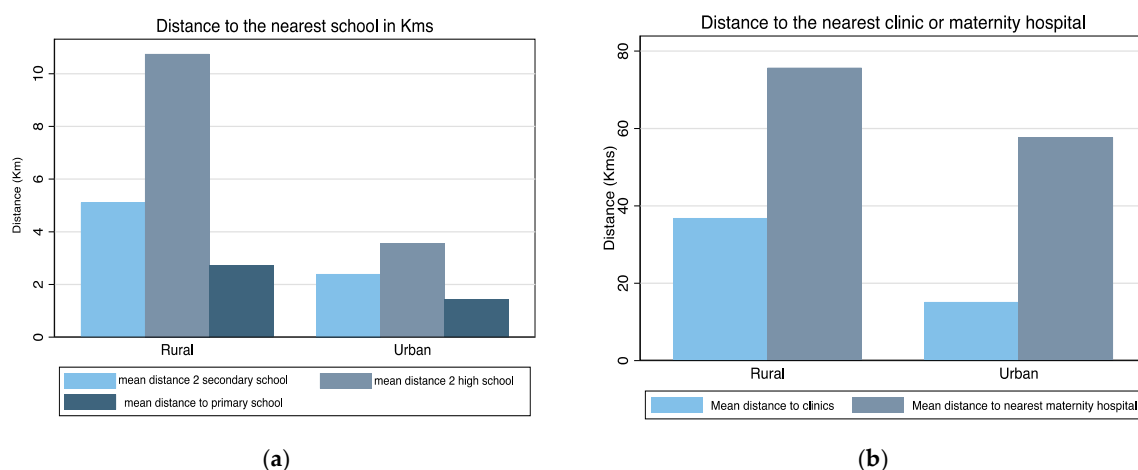


Figure 2. Mean distance to the nearest school (primary, secondary, and high school) and nearest clinic or maternity hospital by rural/urban location in Indonesia. Source: Authors’ calculations.

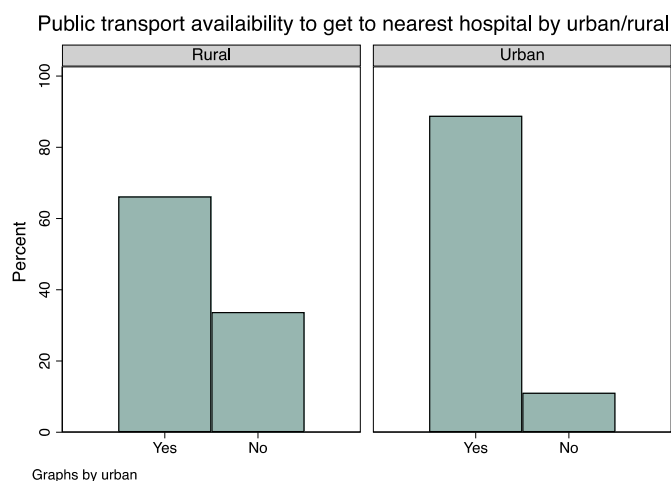


Figure 3. Percentage of households with public transport availability to the nearest hospital by rural/urban location in Indonesia. Source: Authors' calculations.

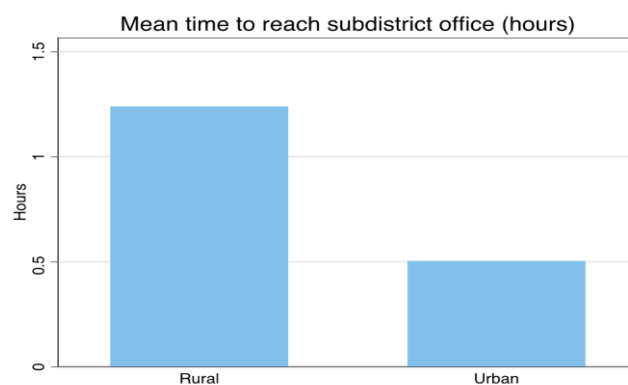


Figure 4. Mean time to the nearest sub-district office by rural/urban location in Indonesia. Source: Authors' calculations.

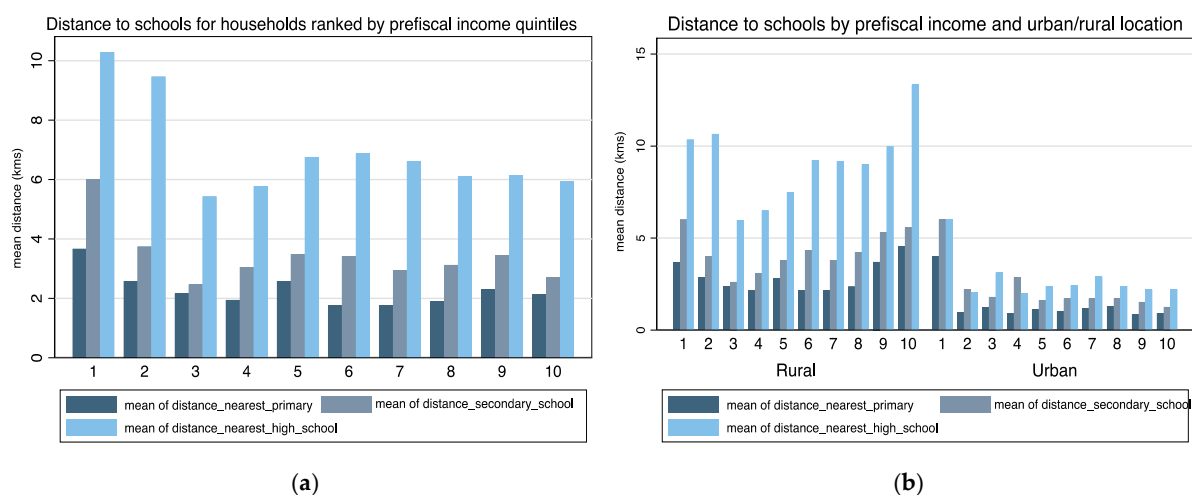


Figure 5. Mean distance to the nearest school (primary, secondary, and high school) by Pre-Fiscal Income decile and by rural/urban location in Indonesia. Source: Authors' calculations.

The somewhat puzzling difference between the rural sample (a U-shaped relationship) and the urban sample (a negative correlation between distance and income) may be attributable at least in part to the smaller number of observations in the urban sample as

compared to the rural sample, given that PODES is primarily a village-level survey. Of course, accessibility is largely conditional on means of travel to the nearest school. Because we do not have information on the means of transport by respondents, we cannot assess the actual impact on transport inequality. Indeed, the specific reason for the rural U-shaped relationship is unknown. It could be that richer households sort into areas where social services are more easily accessible or that there are higher concentrations of richer households in urban areas compared to rural areas. Also, urban travel distances are likely to be shorter than rural distances. Rural households are also more apt to be spread out, with no clear linear relationship between Pre-Fiscal Income and social services.

The relationships between distance and access to other indicators are further examined in Figure 6 (nearest clinic and hospital) and Figure 7 (nearest maternity hospital). Overall, distances to the nearest health facilities such as hospitals, clinics, and village health posts are largely negatively correlated with income, even though this relationship is somewhat weak. There is a significant decline in mean distances to the nearest hospital or clinic as income increases for the lowest four Pre-Fiscal Income deciles (Figure 6a); for the rest of the deciles, the relationship is somewhat erratic but even so the top deciles face shorter distances to these health facilities than the lower deciles. Figure 6b shows that when the sample is divided by urban/rural location, rural households generally have greater distances to health facilities than urban households. Note again that this rural/urban pattern may be due to the smaller sample size of urban households. Figure 7 shows the distribution of access to maternity hospitals by Pre-Fiscal Income (Figure 7a) and also by rural/urban location (Figure 7b). The general pattern once again is that higher-income households tend to face shorter distances to these facilities than lower-income households; similarly, households in rural areas tend to face greater distances to these health facilities than households in urban areas, although this pattern is somewhat variable. Indeed, for urban households, there appears to be an inverted U-shaped relationship between access and Pre-Fiscal Income. In the absence of additional household data, there is no obvious explanation for this inverted U-shaped relationship, although it should be remembered again that we have a small urban sample and so the results here may not be truly representative for all urban households. The overall pattern again is that the lowest-income deciles face a larger distance to these facilities than other deciles. These results indicate that accessibility to social services in terms of distance is associated with household income but that many other unspecified factors might contribute to this relationship.

Overall, it can be concluded that household Pre-Fiscal Income and distances to the nearest health facilities have a largely inverse relationship, with distances generally decreasing as income rises, even though this relationship is not strictly monotonic.

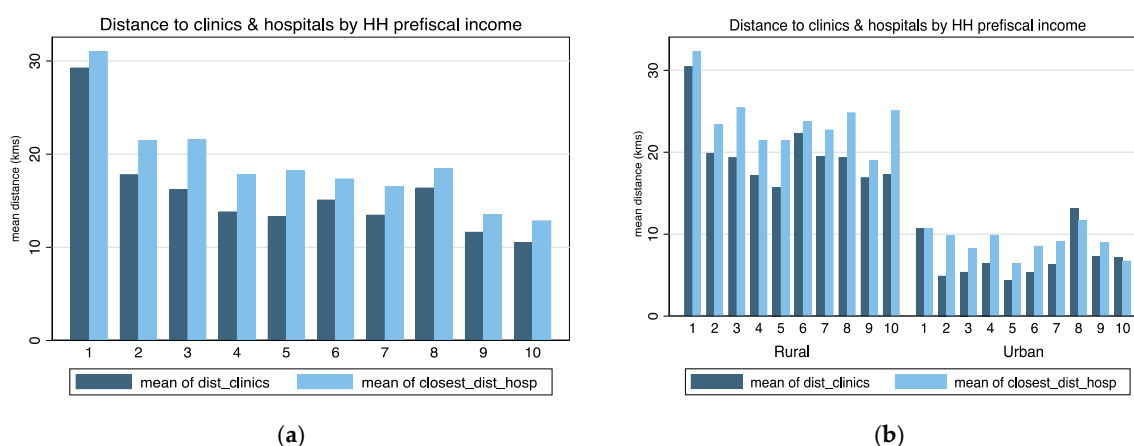


Figure 6. Mean distance to the nearest clinic and hospital by Pre-Fiscal Income decile and by rural/urban location in Indonesia. Source: Authors' calculations.

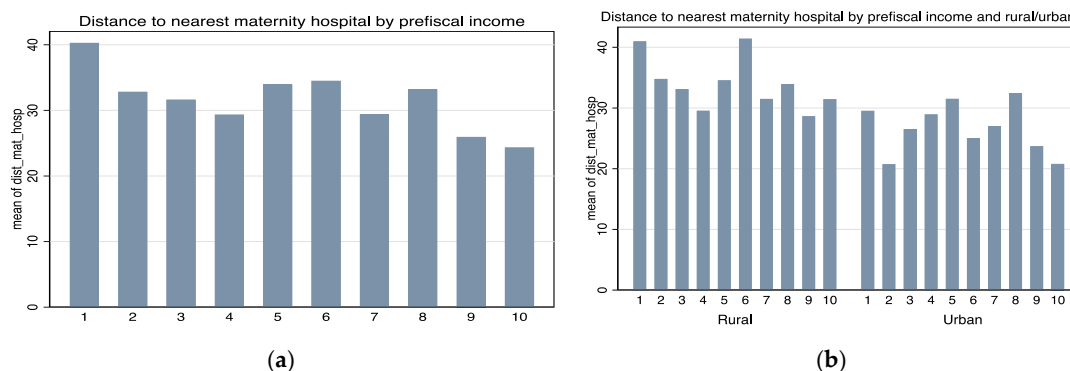


Figure 7. Mean distance to the nearest maternity hospital by Pre-Fiscal Income decile and by rural/urban location in Indonesia. Source: Authors' calculations.

Figure 8 demonstrates the relationships between ease of access to various facilities, distance, and Pre-Fiscal Income. Note that the “ease of access” indicator only measures responses to the question “How easy or difficult is it to get to the nearest facility?”, so that the indicator does not specify whether “easy or difficult” is based on distance, affordability, or mobility. As a result, we cannot disentangle factors that contribute to positive or negative responses. However, since we have the “distance” indicator, we try to investigate the extent to which “distance” contributes to a certain response to the “ease of access” question and its correlation with Pre-Fiscal Income. Figure 8a shows access to the nearest primary school, Figure 8b shows access to the nearest high school, Figure 8c shows access to the nearest hospital, and Figure 8d shows access to the nearest clinic. For distance to the nearest primary school (Figure 8a), income deciles 1 and 2 face difficulty accessing the nearest primary school, even though the mean distance is 10 kms, which suggests that factors other than distance contribute to this response, factors that could be related to affordability or mobility. Moreover, there is a large density of poorer households that face some difficulty in accessing the nearest primary school and simultaneously face larger distances. An even higher density of poorer households responds with “very difficult” when asked about the ease of accessibility to the nearest primary school regardless of distance. This means that, regardless of distance, poorer households face more difficulties in accessing the nearest schools. Similar responses occur regarding ease of access to high school (Figure 8b). As for access to hospitals (Figure 8c) or clinics (Figure 8d), the response “difficult” is uniformly higher for all deciles than the response “easy”. However, for higher-income deciles reporting difficulty in accessing hospitals or clinics, the mean distance is higher than for lower-income deciles reporting difficulty in accessing these facilities. This suggests that poorer households are systematically more likely to be transport-poor along several dimensions even beyond accessibility.

Finally, Figures 9 and 10 show that those least likely to have access to public transportation to schools and hospitals tend to be concentrated in low- to middle-income deciles. Especially striking is Figure 10, which shows that the poorest 20 percent of households are twice more likely to have no access to public transport for accessing the nearest hospital compared to the richest 20 percent.

These many estimates illustrate the insights from the “access indicators approach”, allowing a better understanding of how infrastructure investments may affect households of different income levels by changing the access of households to the nearest clinic, hospital, or school. Our distributional analysis shows that Pre-Fiscal Income is often, if not always, negatively correlated with distance to the nearest school, clinic, or hospital in the overall sample. Moreover, when analyzed by urban/rural location, we find somewhat variable results. For rural households, accessibility is U-shaped in the case of distances to schools. The location of social services could be a function of multiple factors and not just

household sorting based on Pre-Fiscal Income. Moreover, the urban sample in our analysis is much smaller than the rural sample, so disaggregating by rural/urban might not be a valid comparison because sample sizes in rural versus urban areas differ quite significantly.

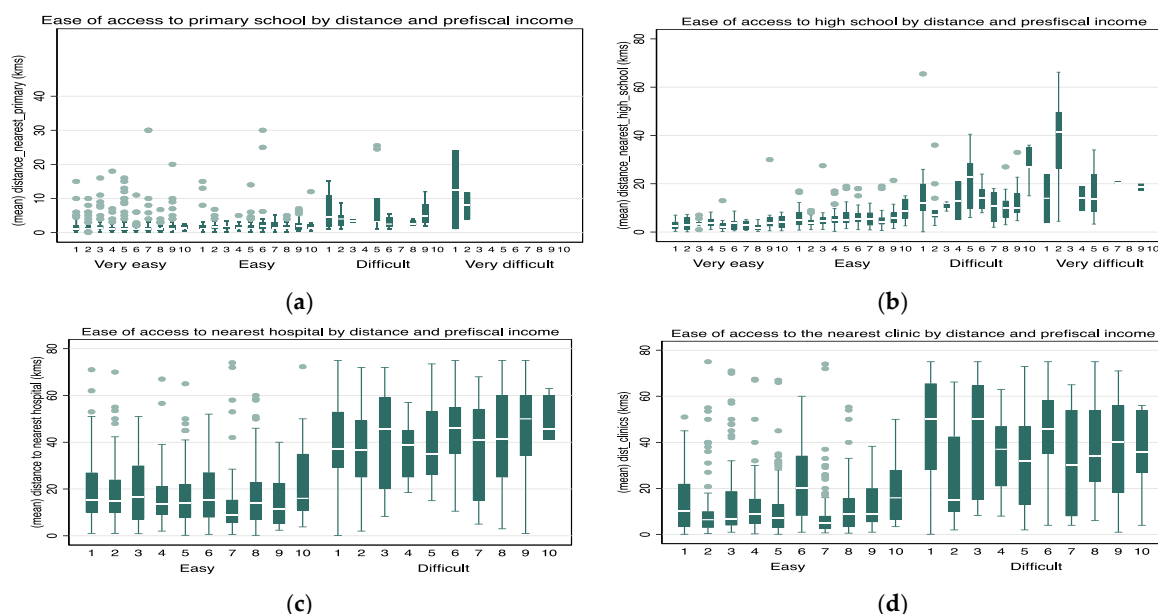


Figure 8. Ease of accessing the nearest primary school, high school, hospital, and clinic by distance and by Pre-Fiscal Income decile in Indonesia. Source: Authors' calculations. The box and whisker plots are graphical representations of the distribution of distance, ease of access, and Pre-Fiscal Income. These allow us to explore how distances relate to Pre-Fiscal Income across different ease-of-access categories. The box represents the interquartile range, the height of the box is proportional to the interquartile range and contains the central 50 percent of the data, and the whiskers extend from the box to the minimum and maximum distances across several access categories. The dots represent outliers.

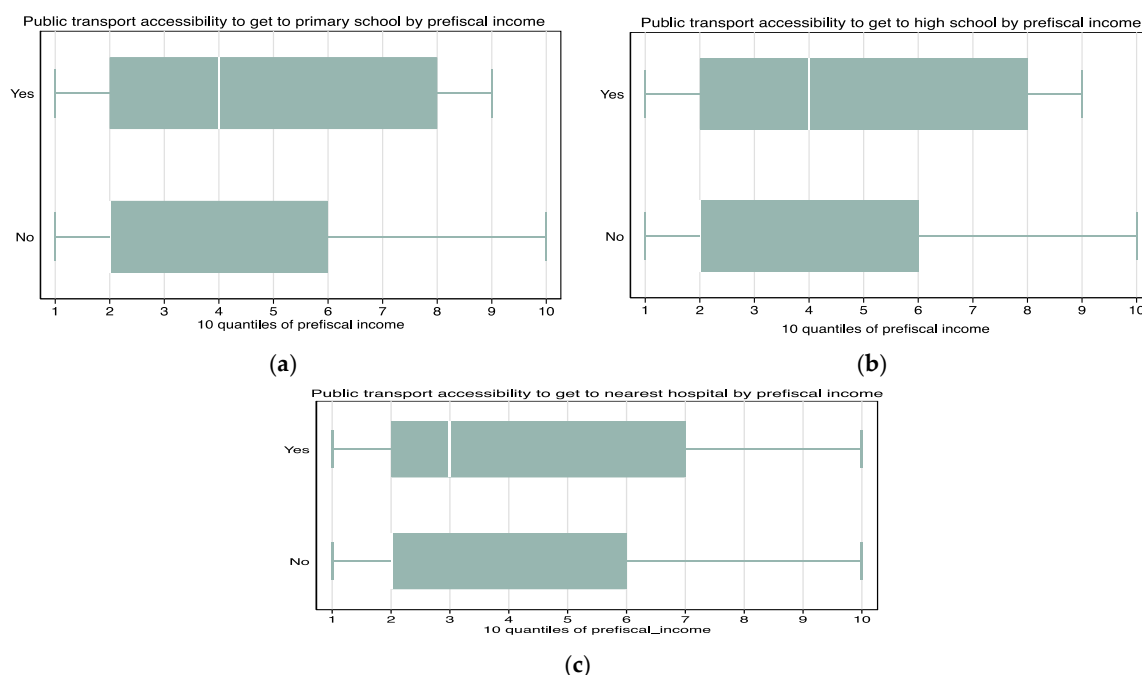


Figure 9. Distribution of public transport accessibility to primary school, high school, and hospital across Pre-Fiscal Income deciles in Indonesia. Source: Authors' calculations.

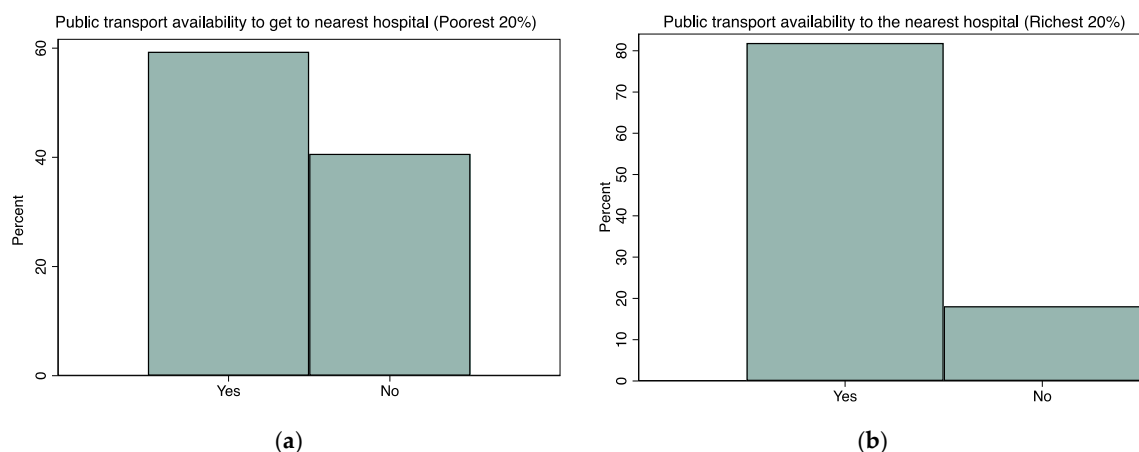


Figure 10. Percentage of households with public transport accessibility to hospitals for poorest 20 percent versus richest 20 percent by Pre-Fiscal Income and by rural/urban location in Indonesia. Source: Authors' calculations.

Even so, the implication of this access indicators approach, at least for Indonesia, is that improvements in transportation infrastructure, especially for lower-income households in rural areas, will often benefit more heavily these households by reducing the disparities in access to essential services across income groups and geographic locations.

4.5. Results: Time-Savings Approach

Applying the time-savings approach is more difficult than applying the access indicators approach. As discussed earlier, the time-savings approach requires several types of information:

- How does a transportation infrastructure project reduce travel times for households?
- How are these time savings valued by households?

We do not have information on the impact of any type of transportation infrastructure project on travel times. However, we do have information that allows us to value for households any time savings that a project may generate, at least for quintiles of Pre-Fiscal Income. In combination with assumptions about the time-savings effects of a typical (or a “generic”) transportation project, we are able to calculate the effects of the generic project on the value of time savings by Pre-Fiscal Income quintiles. Note that we are not able to make these calculations at the individual household level given that our Indonesian survey data are only available by Pre-Fiscal Income quintile. As we discuss later, our Mozambique data allow us to make these calculations at the individual household level, although the Mozambique data have other limitations.

In particular, we make the following specific assumptions. We start by assuming a generic road transportation project that will reduce the travel time across all income groups, measured by income quintile. Travel times are based upon the assumption of an average bus speed of 19.6 kmph. This assumption about travel speed is based upon the analysis of [89] for India, who estimate that the average bus speed on intra-city/town/village roads is 19.6 kmph. Note that the average speed of a bus (or a car) may vary widely depending on factors such as road conditions, traffic density, type of road, weather conditions, and the vehicle's characteristics. In our example, we use only bus speed combined with the assumption that all households use a public bus to gain access to the nearest school or hospital. We further assume that the generic project reduces travel times by either a 25 percent reduction in travel times or a 50 percent reduction, identical across all household Pre-Fiscal Income quintiles. Further, we assume that each one hour of time saved is valued at the household's hourly wage, calculated by household income decile

from the average quintile household monthly income. Finally, we calculate the benefits of the generic project by household Pre-Fiscal Income quintile by the value of the time savings. These assumptions can easily be varied to examine the sensitivity of the results to changes in the assumptions. As only one example, we can make the time reductions equal in absolute time (not percentage) amounts by income quintile.

The results of this analysis are presented in Figures 11 and 12. Figure 11 shows the impact of our generic transportation project on the reductions in travel times to the nearest school (Figure 11a) and to the nearest clinic (Figure 11b). Figure 12 shows the value of these time savings by income quintile.

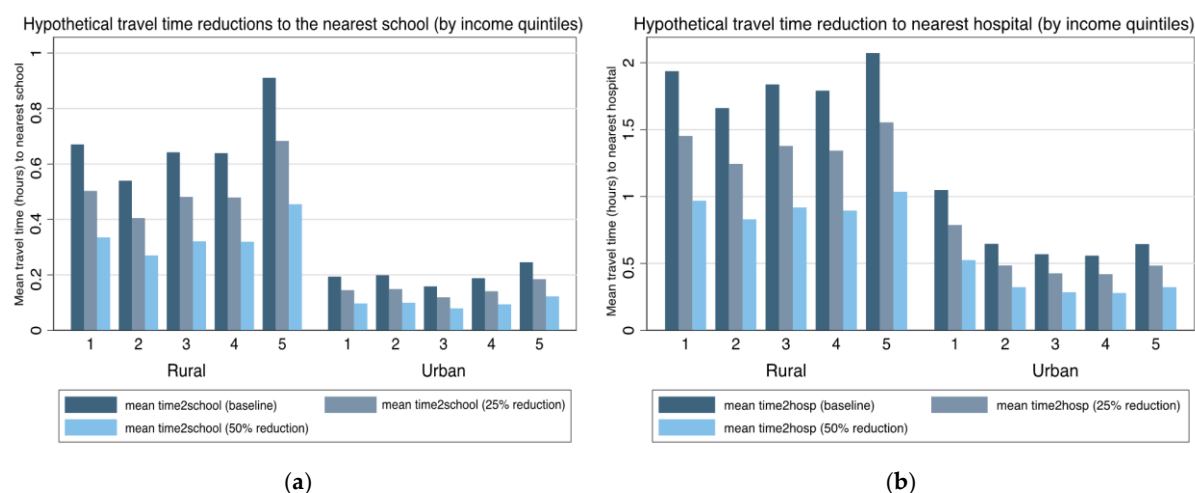


Figure 11. Reductions in travel times to nearest school and hospital by Pre-Fiscal Income quintile and by rural/urban location in Indonesia. Source: Authors' calculations.

Figure 11 demonstrates that the larger time savings are in rural areas versus urban areas. Further, these time savings tend to be slightly larger for higher-income quintiles. Given that higher-income quintiles obviously have a higher calculated hourly wage, the resulting distribution of time savings is decidedly pro-rich, not pro-poor (Figure 12), especially in rural areas.

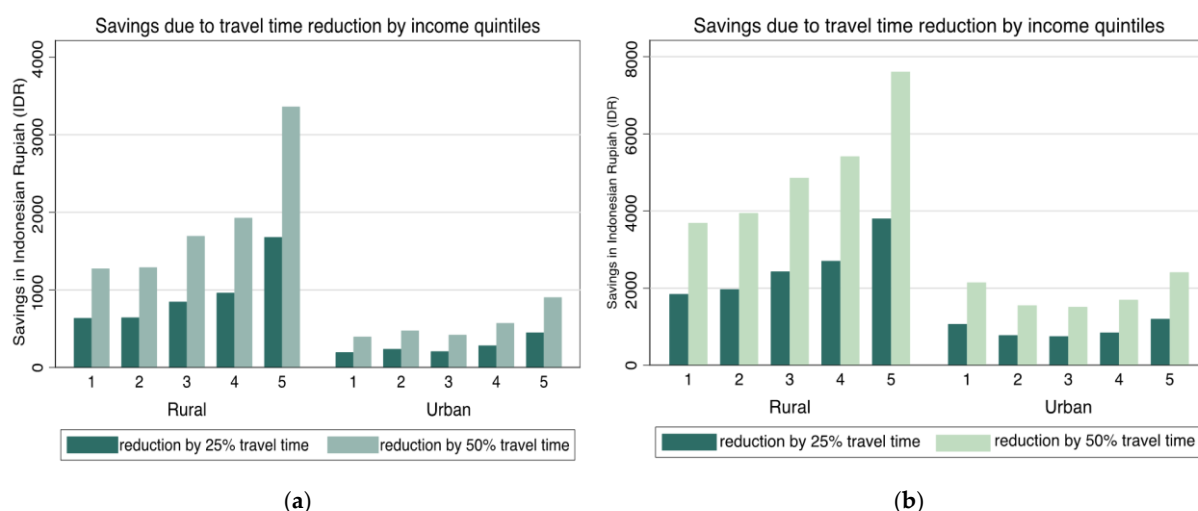


Figure 12. Value of time savings for access to nearest school and hospital by Pre-Fiscal Income quintile and by rural/urban location. Source: Authors' calculations.

4.6. Summary: Indonesia

Admittedly, these results are not overly strong or consistent, due largely to data limitations. Even so, we believe that the results demonstrate several main tendencies. There are significant differences in access to public facilities for households in urban versus rural areas, with households in rural areas often facing more than double the distance facing those in urban areas. There is also a tendency for higher-income households to face shorter travel times to public facilities than lower-income households, although this relationship is a weak one. Finally, a “generic” transportation project generates larger time savings for households in rural areas and larger values of these travel savings for higher-income households overall. Again, however, the relationship between the value of time savings and income is not overly strong.

Despite these somewhat mixed results, we believe that these results illustrate three basic points. First, with appropriate data, we are able to estimate at the household level the travel distance or travel time of these households to various public services (clinics, pharmacies, hospitals, and schools). Second, with appropriate data, we are able to relate these travel times to the income levels of these households. Third, for any specific transportation infrastructure project that changes these travel times in a well-defined way, we are able to estimate the benefits of these improvements in transportation in reduced travel distance or travel time by the income levels of these households and then convert these time savings into monetary values. Put differently, and more broadly, we are able to allocate to households of different income levels the non-monetary and especially the monetary benefits of at least some categories of government expenditures—those on transportation infrastructure—thereby extending benefit incidence studies to government infrastructure spending.

5. Application 2: The Distributional Effects of Road Infrastructure Investments in Zambezia, Mozambique

Our second application also uses the methodology presented in the earlier discussion, especially the geo-spatial aspects of this methodology, to examine the distribution of travel time to schools, clinics, and markets for households in the Zambezia province of Mozambique. We draw upon a Mozambique dataset constructed using the national household survey, along with a special geo-spatial dataset on travel distances and times provided by Environmental Resource Management (ERM). See [90] for further discussion of this dataset. ERM is the world’s largest sustainability advisory firm, and it frequently conducts geo-spatial analyses for a variety of sustainability projects. The ERM geo-spatial data allow us to investigate the relationship between household Pre-Fiscal Income and travel times to the nearest schools, clinics, and markets across income deciles.

It should be noted and emphasized that our data for Mozambique have some significant limitations, which make applying the access indicators approach and especially the time-savings approach challenging. ERM provided geo-spatial walking distance and driving time estimates in four broad categories of walking distance and driving time, as shown in Table 1, below; see also Figure 13. While valuable, these data do not provide sufficient detail at the household level to allow a full and accurate distributional analysis of time and distance across income deciles for the time-savings approach, even though we attempt these calculations later. In particular, 80 to 90 percent of the households in the ERM data are assigned the same “driving time”, and it is therefore challenging—indeed, virtually impossible—to explore variation in driving times across Pre-Fiscal Income deciles. While geo-spatial data calculated by ERM are more accurate relative to survey data because satellite-calculated data have lower chances of measurement error, the ERM driving time data do not have the level of granularity and especially the amount of variation

across households needed for more accurate representation at the household level. It should also be noted and emphasized that the income dataset for all of Mozambique may not accurately represent the specific province of Zambezia, given that this dataset was designed to be representative only at the national level and not for individual provinces. Nevertheless, we believe that both the access indicators approach and the time-savings approach provide some useful insights into the ways in which our methods can be applied; that is, combining geo-spatial distance and time data with household income data is able to provide distributional information for a BIS, but this analysis requires that more granular data become available to be most useful. In any event, one should use the results that follow with some caution given these data limitations.

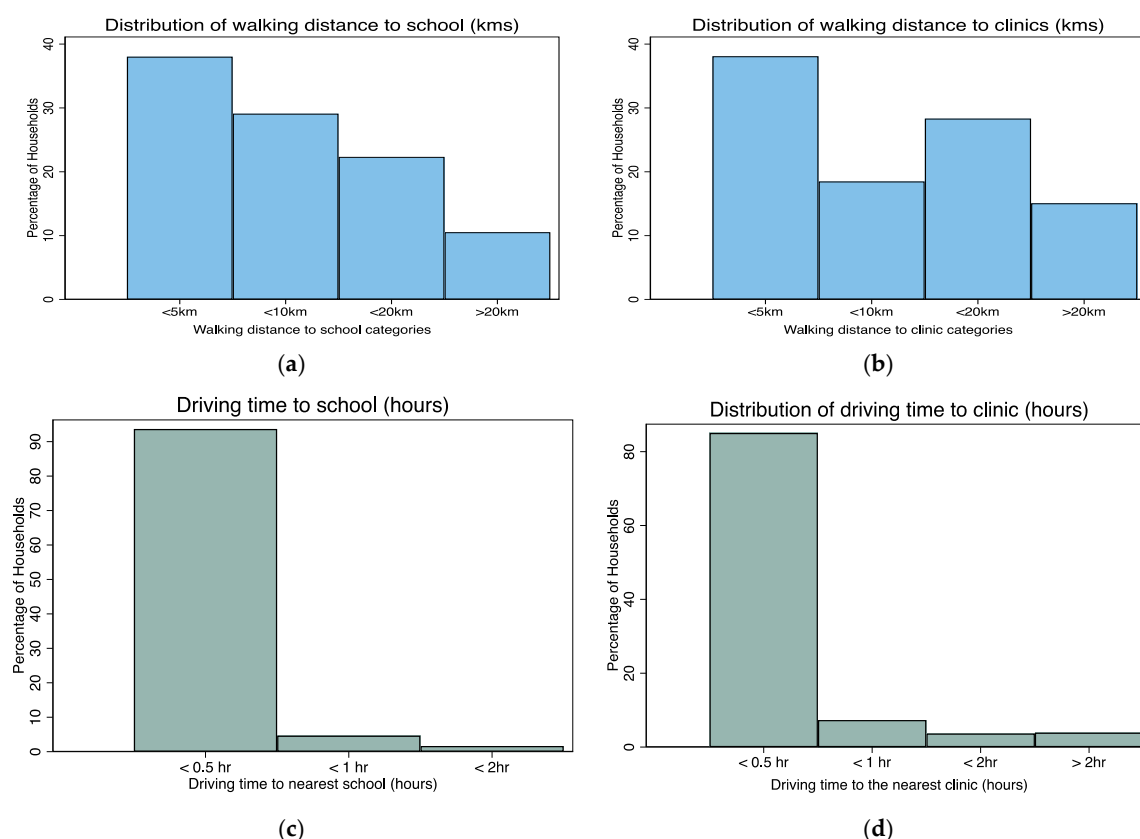


Figure 13. Walking distance (kms) and driving time (hrs) categories for schools and clinics in Zambezia. Source: Authors' calculations.

Table 1. ERM travel time and distance categories in Zambezia.

Category	Driving Time (hrs)	Walking Distance (kms)
1	Less than 30 min	Less than 5 kms
2	Less than 1 hr but more than 30 min	Less than 10 kms but more than 5 kms
3	Less than 2 hrs but more than 1 hr	Less than 20 kms but more than 10 kms
4	Over 2 hrs	Over 20 kms

Source: Authors' calculations.

5.1. Data

We use two main data sources. The first is a geo-spatial dataset on walking distance and driving time to the nearest school and clinic based on household longitude and latitude locations, provided by Environmental Resource Management (ERM). See <https://www.erm.com/about/> (accessed on 1 February 2026). Data shared by ERM provide the walking distance and driving time to the nearest school or clinic based on the 1 × 1 km

(sq) grid travel time, calculated as the time taken to travel from point A to point B. Second, we use the income dataset for Mozambique constructed using the 2020 National Household Survey dataset for Mozambique, derived from [90]. Again, it is important to remember the limitations of these datasets.

5.2. Methods

Using the geo-spatial data provided by ERM in combination with the Mozambique National Household Survey for 2020, we first located households with specific longitude/latitude geo-spatial locations. We used their location to obtain the walking distance and the driving time to relevant facilities for each household. We then merged this information with our income dataset. Our objective is to assess the travel “costs” in terms of time and distance traveled, based on socioeconomic characteristics such as deciles of Pre-Fiscal Income. Using these various income concepts and relating them to travel “costs” can give us the capability of identifying where infrastructure investments should be targeted to reduce differentials by income in access to infrastructure.

As noted above, our first step was to locate households with specific longitude/latitude geo-spatial locations. We provided ERM with an initial dataset consisting of each household’s enumeration area and longitude/latitude locations using the Mozambique household survey data. ERM then used these geo-coded locations to obtain the walking distance and driving time to the nearest school or clinic by running a network analysis to generate travel time layers to schools and clinics. Specifically, ERM converted the survey records (in longitude/latitude locations) to GIS format and used travel time layers in order to calculate for each unique survey record (or each unique household) the categorical travel time to different services.

Since the income dataset was created using the National Household Survey, we added a layer of geo-location that was part of the National Household Survey. We then merged the ERM geo-spatial dataset with the income dataset using household geo-location (longitude/latitude) as the common identifier.

Our final merged dataset consisted of 1433 observations at the household level for Zambezia Province. This dataset included information on income, walking distance to the nearest school/clinic/market, and driving time to the nearest school/clinic/market. We were able to match successfully 88 percent of household geo-locations from the ERM dataset with the income dataset. ERM’s final dataset consists of households with an assigned category based on Table 1, in which ERM used a network analysis of “walking (kms) to clinics” and “driving (hrs) to clinics” to determine categories for households in Zambezia. This dataset was merged with the income dataset to generate a final household level dataset with income concepts and driving time and walking distance to schools and clinics.

5.3. Results: Distribution of Income

Mozambique has high levels of income inequality across the entire country, and the fiscal system is not equalizing, as demonstrated by our calculation of a Pre-Fiscal Income Gini index for Mozambique of 0.5852 and a Consumable Income Gini index of 0.5511. Figure 14 shows the distribution of income in all of Mozambique versus the province of Zambezia. Figure 15 demonstrates that rural Mozambique has a fairly flat distribution of income as compared to urban areas. In both Figures 14 and 15, the red dotted line shows the average income for all of Mozambique. However, in rural Zambezia, low-income deciles are overrepresented, while in urban Zambezia, low-income deciles are underrepresented. Similarly, Figure 16 shows that urban poor are overrepresented in Zambezia as compared to the rest of the country as measured by headcount poverty. Thus, Zambezia is not entirely representative of Mozambique, and our results should be treated with some caution.

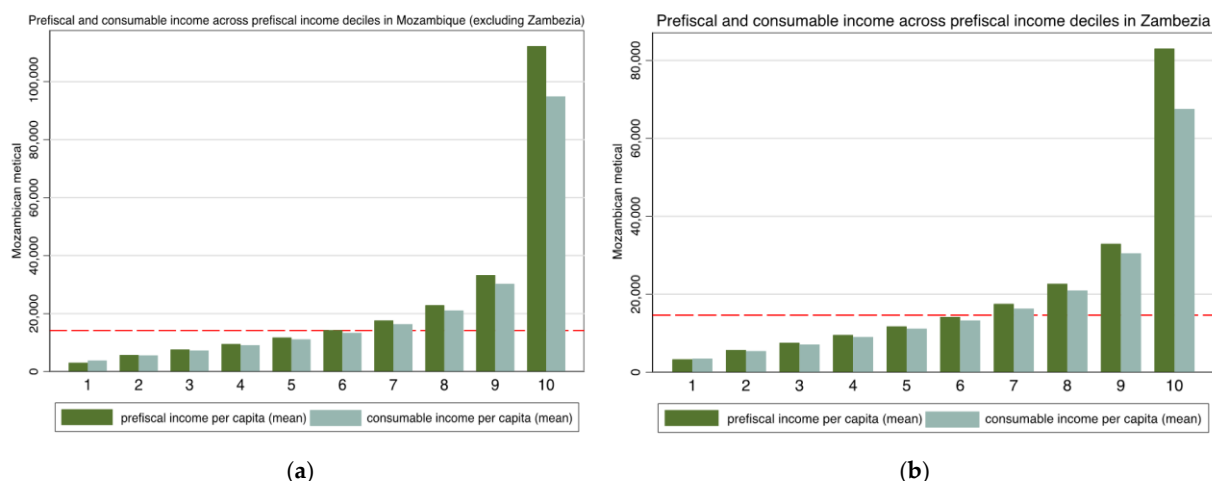


Figure 14. Pre-Fiscal and Consumable Income and by urban/rural location in all of Mozambique versus Zambezia. Source: Authors' calculations.

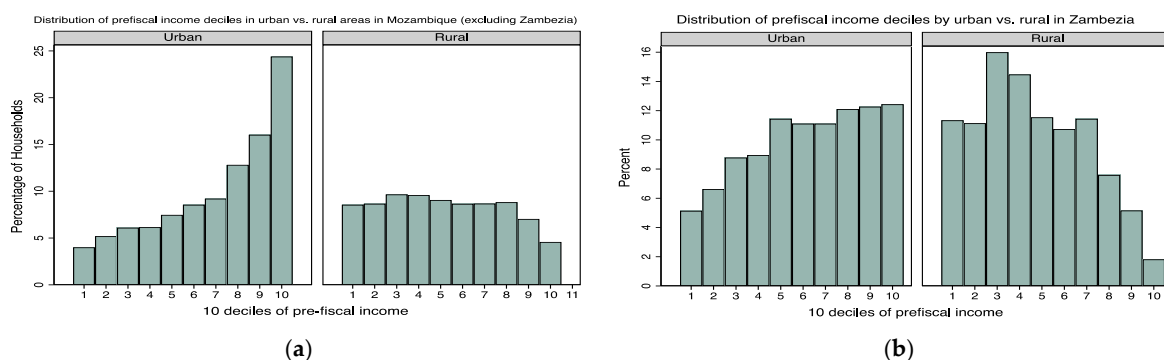


Figure 15. Distribution of Pre-Fiscal Income deciles by urban/rural location in all of Mozambique versus Zambezia. Source: Authors' calculations.

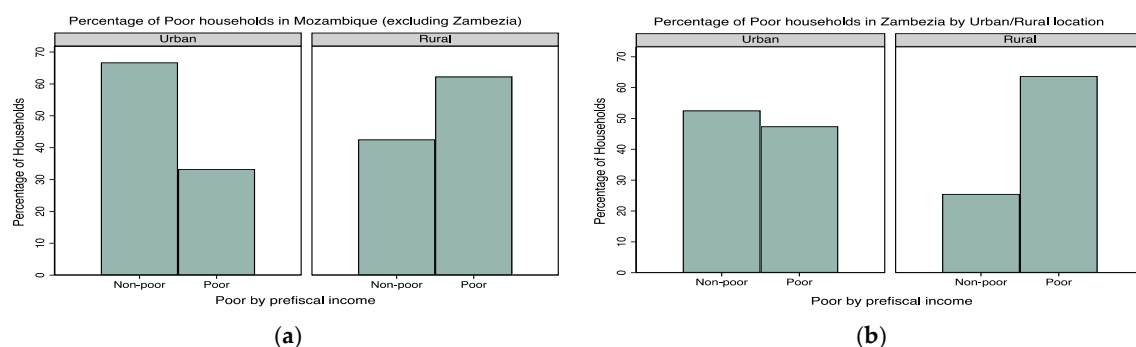


Figure 16. Percentage of poor households (poverty headcount) by urban/rural location in all of Mozambique versus Zambezia. Source: Authors' calculations.

5.4. Results: Access Indicators Approach

We analyze household access to schools and clinics, measured by the walking distance and driving time of households in Zambezia to the nearest school or clinic (the access indicators approach). For schools and clinics, we present the results by different income deciles and by rural/urban location. We also examine driving time to the nearest market by income and by rural/urban location.

Consider first the average walking distance to the nearest school or clinic (kms) by rural/urban location (Figure 17). Urban households on average face similar walking distances to schools as rural households. This shows that schools are more evenly spread out

across communities of households regardless of whether they are in urban or rural areas. However, in both cases the mean walking distance is close to 10 kms, which is a considerable distance to cover while walking to school. In contrast, the walking distance to the nearest clinic for rural households is more than twice that of the walking distance to the nearest clinic for urban households.

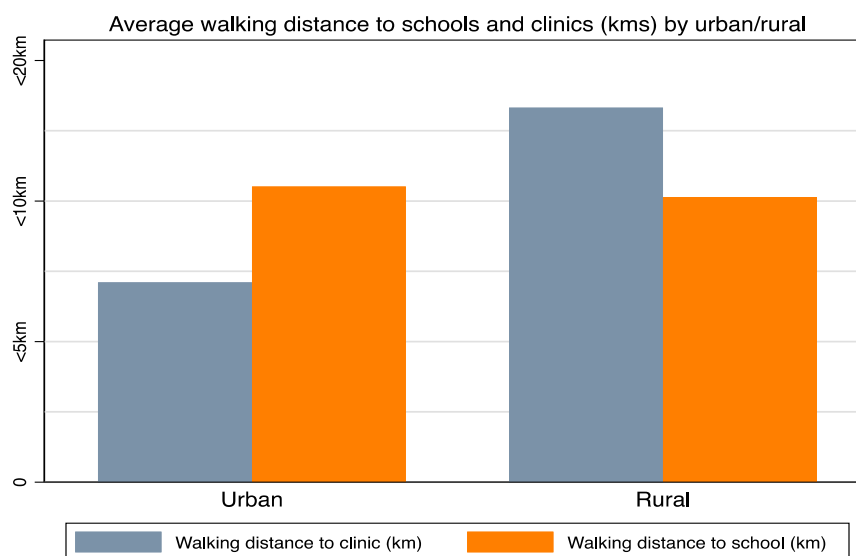


Figure 17. Walking distance (kms) to the nearest school or clinic by rural/urban location in Zambia. Source: Authors' calculations.

Consider next the walking distance to the nearest school or clinic for the poorest 20 percent versus the richest 20 percent (by Pre-Fiscal Income) and by urban/rural location (Figure 18). As shown in Figure 18a, the poorest 20 percent live closer to schools in urban areas, with 65 percent facing distances that are less than 10 kms. However, in rural areas, the poorest 20 percent are more likely to face wide variation in walking distance to schools. Similarly, in urban and rural areas, 70 percent of the richest 20 percent of households can reach schools within 10 kms. However, almost 40 percent of the richest 20 percent of households still face significantly long distances to clinics in rural areas. In terms of walking distances to the nearest clinics, 85 percent of the richest 20 percent can reach a clinic within 10 kms; however, the accessibility to clinics in rural areas shows wider variation. In rural areas, even the richest 20 percent have to travel long distances to reach clinics (Figure 18d). In urban areas, the poorest 20 percent face similar distances to the nearest clinic as the rich (Figure 18c). In fact, the distributions are quite similar for both categories, indicating that clinics are easily accessible in urban areas regardless of Pre-Fiscal Income, while in rural areas clinics are more spread out.

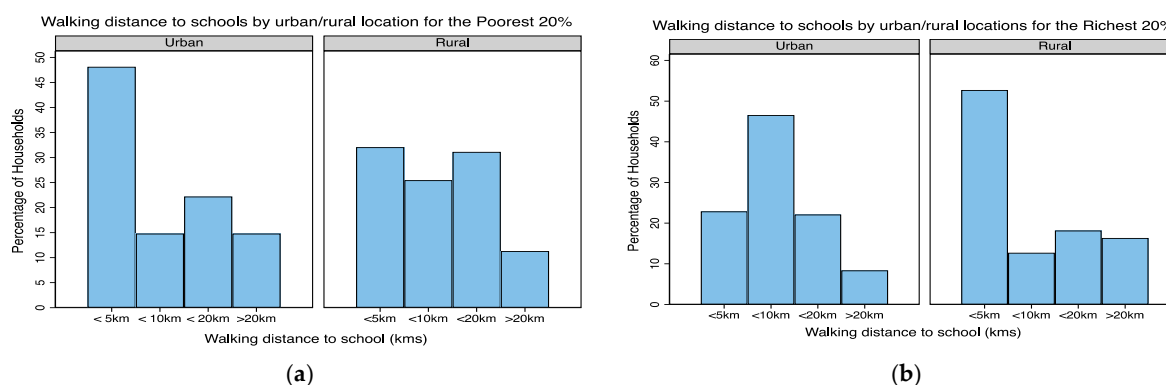




Figure 18. Walking distance (kms) to the nearest school and the nearest clinic by rural/urban location in Zambia for poorest 20 percent versus richest 20 percent. Source: Authors' calculations.

We find broadly similar results when we examine the walking distance to the nearest school or clinic relative to Pre-Fiscal Income deciles and by rural/urban location (Figure 19a). When we examine the driving time to the nearest school or clinic by Pre-Fiscal Income decile and by rural/urban location, we see somewhat different patterns (Figure 19b). The average driving time to the nearest school is less than 30 min for all urban households regardless of their income decile, and the average driving time to the nearest clinic is also close to 30 min for most deciles, except for the top three deciles, for whom the driving time is slightly greater. For rural households, the average driving time to the nearest school is also roughly 30 min for most deciles. In contrast, the average driving time to the nearest clinic for rural households is higher than for urban households (between 30 and 60 min), with a slight tendency for this value to rise with income.

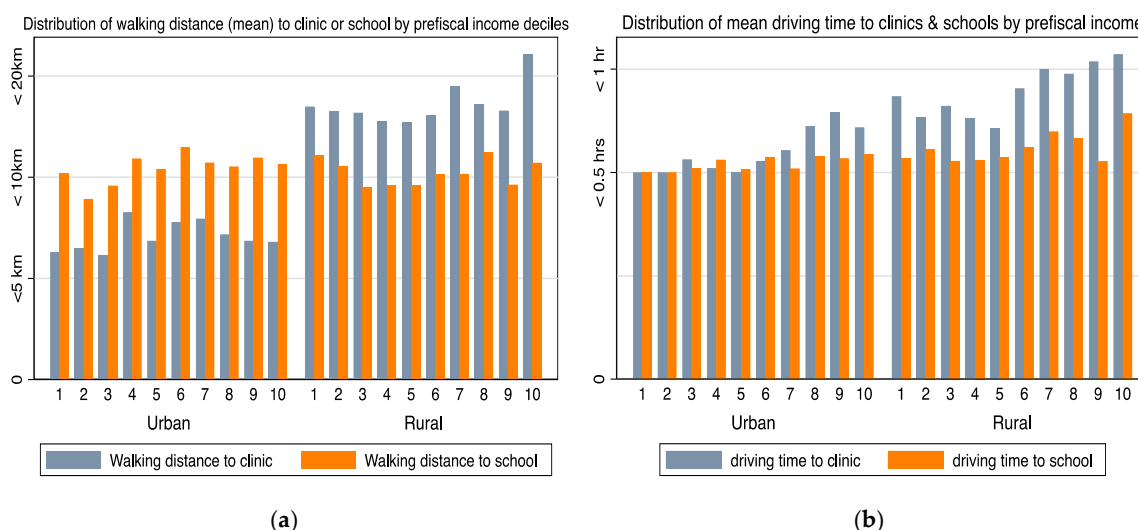


Figure 19. Walking distance (kms) and driving time (hrs) to the nearest school or clinic by Pre-Fiscal Income decile and by rural/urban location in Zambia. Source: Authors' calculations.

The distribution of travel times to markets of different sizes in terms of populations (50,000, 100,000 200,000 and 500,000) is shown in Figure 20 by Pre-Fiscal Income decile (Figure 20a) and by rural/urban location (Figure 20b). In general, rural households face longer travel times than urban households, especially to larger markets. Of note, travel times to markets tend to be longer for lower-income-decile households, regardless of market size. Travel times to markets of 200,000 and under for the poorest 10 percent are more

than twice the time for the richest 10 percent. Nevertheless, there is considerable variation in travel times across all households, whether by rural versus urban, by income decile, or by market size.

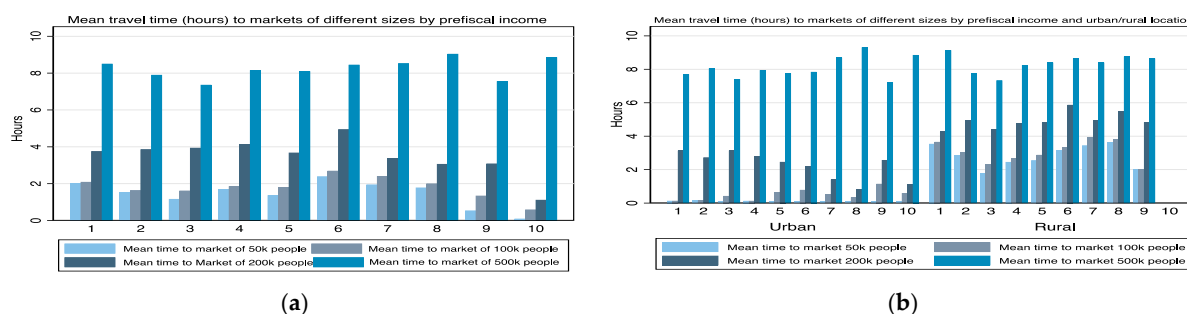


Figure 20. Travel time (hrs) to the nearest markets of different sizes by Pre-Fiscal Income decile and by rural/urban location in Zambezia. Source: Authors' calculations.

To repeat our cautionary note, as Lucas et al. (2016) [74] and others argue, transport poverty does not have a single dimension, and we need granular and high-quality data on accessibility, affordability, and mobility to measure transport poverty accurately and fully, especially when we are interested in distributional effects. Unfortunately, we do not have this kind of granularity, which makes it difficult to relate distances and times to household income levels. As a result, these results must be taken as an initial effort and with some caution. Even so, we believe that these results demonstrate the potential of our time-savings approach to make a more definitive assessment of the relationship between travel “costs” and income in Zambezia, especially if more complete household data were to become available.

The accessibility estimates for the Zambezia province of Mozambique indicate that accessibility indicators are negatively correlated with Pre-Fiscal Income, even if this relationship is weak. However, this might not always be the case across all Mozambique provinces, especially those in rural areas where households are located further away from hospitals and schools, and where richer households may in fact face longer distances to these facilities. Having access to motorized vehicles drastically reduces the effective distances to social services; however, we do not have data on vehicle ownership. More generally, we emphasize again that the quality of the geo-spatial data that we used makes our analysis more difficult and our conclusions less definitive, even if our methods remain applicable and useful.

These considerations suggest that any analysis will be highly country- and context-specific, such that more disaggregated data will be needed on households located around the radii of roads. Detailed data on travel paths, frequencies, and modes of transport used by households for accessing social services and markets will also be required. Such data will enable a more robust distributional analysis of potential infrastructure investment projects. Furthermore, policymakers will need to assess whether households in a particular location are facing road infrastructure deprivation or simply school/clinic/marketplace deprivation. Availability of disaggregated data at the local level can help policymakers both identify the type of deprivation and analyze distributional costs and benefits of public projects. Our analysis is meant to provide a basic framework for how to measure the distributional impact of a potential infrastructure project. The first step is to identify the existing distribution of infrastructure access indicators by income deciles, as we have done here. The next step is to simulate these distributions post-investment, a step that we have not done here. Even so, there are many additional steps needed to fully incorporate our methods in a benefit incidence study. These next steps are discussed later.

5.5. Results: Time-Savings Approach

The time-savings approach requires more information than the access indicators approach, especially information on (1) how a transportation infrastructure project reduces travel times for households and (2) information on how these time savings are valued by households. Regarding the second issue, we again use information from the income dataset to calculate an hourly wage for all households within each income decile. Regarding the first issue, we again assume the hypothetical existence of a typical (or a “generic”) project that reduces travel time by assumed amounts. However, as noted earlier, the ERM data have some significant limitations. It might appear that the ERM data would enable us to readily calculate time savings, given that these data provide the walking distance and especially the driving time to the nearest school or clinic, along with the driving time to the nearest market, all at the household level for the Zambezia province. In principle, this driving time information, in combination with the assumed reductions in travel time and the estimated hourly wage, would allow time savings to be easily calculated and valued at the household level. However, the driving time information is not very useful for the application of the time-savings approach because nearly all households are assigned the same driving time, so that any assumed reductions in travel time would be identical across households. It is possible of course that this may be an accurate representation of the travel time effects of our generic transportation project. However, we believe that this lack of variation is a significant limitation of these data. As a result, we focus instead on the ERM walking distance information in order to generate estimates of household time savings because the walking distance information exhibits significant variation across households.

More precisely, we make the following assumptions. We start by assuming a generic road transportation project that will reduce the travel time across all household Pre-Fiscal Income deciles by either a 25 percent reduction in travel times or a 50 percent reduction. Travel times are based upon the assumption of an average walking speed of 4.8 kmph; the distribution of walking distance and the assumed reductions in walking distance from our generic project are given in Table 2. Further, we assume that each one hour of time saved is valued at the household’s hourly wage, calculated by household income decile from the average decile household monthly income. Finally, we calculate the benefits of the generic project by household Pre-Fiscal Income decile by the value of the time savings. These assumptions can again easily be varied to examine the sensitivity of the results to changes in the assumptions. For example, we assume in an alternative calculation that the time reductions are equal in absolute time (not percentage) amounts by income decile. The results of this analysis are presented in Figures 21 and 22.

Table 2. Walking distance and assumed time reductions in Zambezia.

Category	Walking Distance (kms)	Assumed Distance (kms)	Walking Time (hrs)	Assumed Reduction in Walking Time (5–10 min per km)
1	Less than 5 kms	3.5 kms	0.73 hrs	0.44 hrs (reduce 5 min per km)
2	Less than 10 kms but more than 5 kms	7 kms	1.56 hrs	0.98 hrs (reduce 5 min per km)
3	Less than 20 kms but more than 10 kms	15 kms	3 hrs	0.5 hrs (reduce 10 min per km)
4	Over 20 kms	23 kms	5 hrs	1.16 hrs (reduce 10 min per km)

Source: Authors’ calculations.

The results of this analysis are presented in Figures 21 and 22. Figure 21 shows the assumed reduction in travel time to schools (Figure 21a) and to clinics (Figure 21b) by Pre-Fiscal Income and by rural/urban location. There is little correlation between travel time reductions and income for schools; also, there is little difference between travel time reductions by rural/urban location. These results are likely due to the proximity of households to schools, whether in rural locations or in urban locations. The results for travel time reductions to clinics also show little correlation with income. However, these reductions are significantly greater for rural households. As for the monetary value of these travel time reductions, the value of the time savings is significantly greater as the household income decile increases, largely because the time savings in hours are largely similar across income groups but the value of these time savings increases with the estimated hourly wage. See Figure 22.

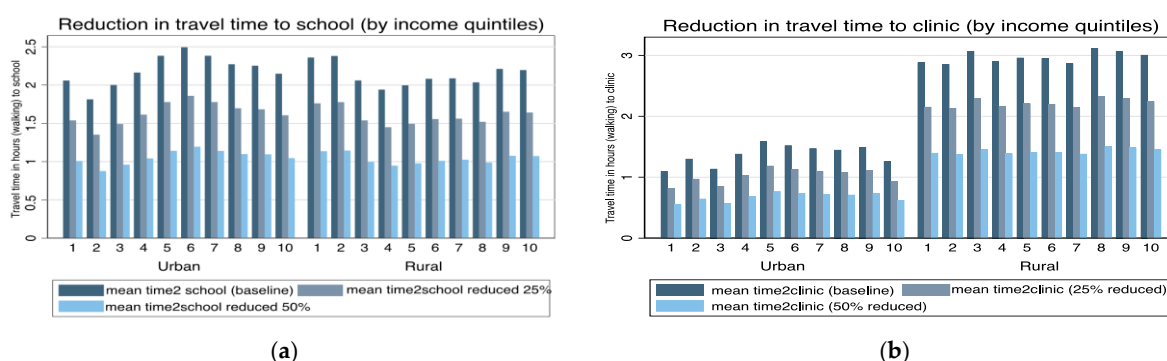


Figure 21. Reductions in travel time to nearest school and nearest clinic by Pre-Fiscal Income decile and by rural/urban location in Zambezia. Source: Authors' calculations.

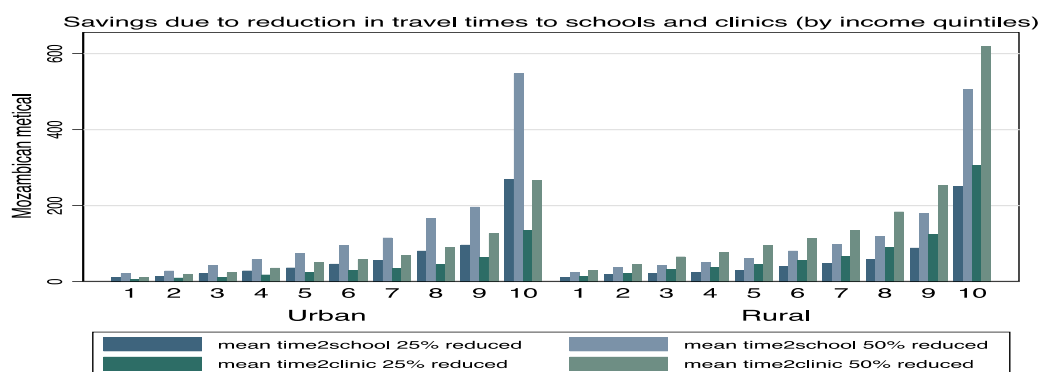


Figure 22. Value of time savings to nearest school or clinic by Pre-Fiscal Income decile and by rural/urban location in Zambezia. Source: Authors' calculations.

Overall, the value of the time savings exhibits a distinctly pro-rich pattern, both in rural areas and in urban areas, because distance and time to services are not strongly correlated with income. These results from the time-savings approach are in contrast to the more pro-poor pattern of the distribution of access indicators.

Note that we continue to find a pro-rich pattern of time savings even when we make an alternative assumption about the time savings of our generic transportation project. When we assume that the time savings from the hypothetical transportation project are an equal absolute amount per km of travel time (e.g., 15 min per km), the resulting value of time savings to the nearest school or clinic by income decile and by rural/urban location is shown in Figure 23. As before, the distributional effects of the hypothetical transportation are pro-rich both in rural areas and in urban areas.

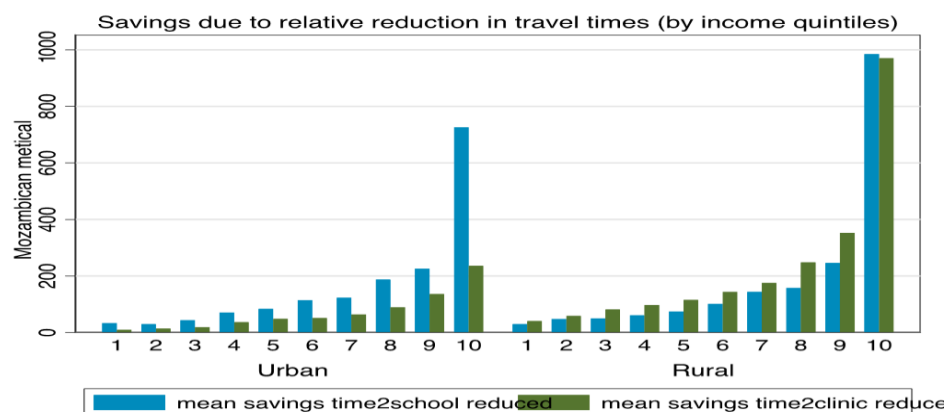


Figure 23. Value of time savings to nearest school or clinic by Pre-Fiscal Income decile and by rural/urban location in Zambezia with equal absolute amount of time savings per km traveled. Source: Authors' calculations.

5.6. Summary: Zambezia

Like the results for Indonesia, the Zambezia results are also somewhat mixed, again due to data limitations. Still, the access indicators approach indicates that the walking distance to schools is roughly the same for rural and urban households (and quite large in both cases), while the walking distance to clinics for rural households is double that for urban households. Also, most income groups in rural and urban areas often face long walking distances to schools and clinics, with no strong pattern by income level, even though there is a weak tendency for lower-income groups to face somewhat longer walking distances to schools or clinics. Somewhat surprisingly, the driving time to schools and clinics is largely the same for poorer and richer households, at least in urban areas. Further, given that a “generic” transportation project results in travel time reductions that are largely the same across income levels, the value of these time savings increases with income because of larger hourly wages for high-income households.

Despite these mixed results for Indonesia and Zambezia, we nevertheless believe that these results are valuable in their own right because they demonstrate the specific ways in which access to public services (as measured by distance or time) varies by rural versus urban location and also by income class. Importantly, these results in both cases show that the reductions in time savings due to transportation infrastructure projects can be converted—with appropriate assumptions—to estimates of their monetary value, a conversion that is necessary for any BIS. Even so, additional steps are needed for a full BIS, as we discuss next.

6. Next Steps

Despite the value of these country-specific results, we believe that there are additional steps that must be taken before a full benefit incidence study can be completed. Some of these steps require more granular geo-spatial data than the data that we used, as we have highlighted throughout our discussion. Some of these steps also require a more complete analytical framework. We focus on the analytical framework in our discussion.

First, it is necessary to estimate the impact of any specific transportation infrastructure improvement in terms of reduced travel time and/or reduced travel distance. Engineering estimates of reduced time/distance should be possible, but these estimates are still a challenge. *Second, and perhaps more importantly, it is necessary to convert any estimates of reduced travel time and/or reduced travel distance from a specific transportation infrastructure project to monetary estimates of the benefits to the households.* In order to monetize these estimates, we need to

estimate the value to households of the time and/or the distance reductions. Our calculations for Indonesia and for Mozambique show that these calculations can in fact be made.

Even so, providing such estimates is not straightforward. Consider time savings. Does one value time by, say, the implicit market wage of the households? Does one adjust the market wage for any taxes, market interventions (e.g., a minimum wage), or market imperfections (e.g., market power)? Does one adjust the market wage for non-monetary aspects of the work versus leisure decisions? Does one adjust the market wage for the presence of unemployment? Instead of using the market wage, does one attempt to estimate the individual's revealed preference for the time reductions as demonstrated in other market choices? Does one attempt to estimate the individual's time valuation by asking them via a survey (e.g., "contingent valuation" methods)? How does one estimate the implications of distance reduction for time reduction? If time and/or distance reductions also lead to a reduction in the risk of travel via reduced fatalities or injuries, does one include the "value of a life" as an additional benefit of the transportation infrastructure, where many questions like those for time valuation also arise?

There are no easy answers to these questions. Even so, there are well-established methods in cost–benefit analysis for valuing time and distance, and also for valuing life. For methods for valuing time savings, see [91–94]. For methods for valuing life savings, see [95–98]. . For a recent general treatment of these and many other measurement issues in cost–benefit analysis, along with detailed references, see [99]. Applying these methods is the next, and essential, step in extending more fully and completely fiscal incidence analysis to government infrastructure spending. Applying these methods also requires more detailed geo-spatial data at the household level than the data that we utilized here. In future work we hope to obtain such detailed geo-spatial data and then to apply the methods that we have developed here.

Still, putting aside the challenges of monetizing the value of time and distance reductions from infrastructure improvements, there are some cautionary notes on these extensions of BIS methods for infrastructure spending.

First, benefit incidence studies of infrastructure investments require a number of assumptions to be made, especially about who benefits from the investments—and the sensitivity of results to these assumptions must be examined. As only one example, it seems reasonable to use the assumption that households closer to a road will be the primary users. However, this may not be an entirely accurate assumption, even if it seems a reasonable assumption to start the analysis.

Second, there are likely distributional effects from the construction per se of infrastructure (e.g., Who works on the construction? Are there multiplier effects?), as distinct from the effects on the flow of services from the completed infrastructure construction. These effects are important, but these one-time effects are appropriately considered mainly in cost–benefit analysis of the construction.

Third, analyzing one part of the expenditure system in isolation of other parts can give misleading results, just as analyzing one part of the tax system in isolation of the entire tax system can give misleading results. The incidence of a single program almost certainly depends upon both its features and those of all other programs.

Fourth, there is much scope for improving the basic BIS methodology in its application to infrastructure investments and for combining it with other, more modern and more theoretically grounded approaches, including those on the valuation of non-market goods (e.g., contingent valuation methods, revealed preference methods, and hedonic methods), as suggested by [42].

Fifth, even if the "true" value of infrastructure investments cannot be measured and allocated to individuals, BIS may still give useful insights, as suggested by the access indicators approach and also by the time-savings approach. If the analysis indicates that

(say) poor households use the outputs of infrastructure projects more intensively than non-poor households, then we know that providing such infrastructure will be pro-poor even if we cannot precisely estimate these distributional effects.

7. Conclusions

Valuing and allocating the benefits of public goods like transportation infrastructure investments is not a simple exercise. Even so, our theoretical framework, together with our empirical applications of this framework to Indonesia and to Mozambique, demonstrates that it is possible to make progress on this benefit incidence study exercise, even if additional work is needed to bring this exercise to a more satisfying conclusion. Especially important in this additional work is the construction of a more complete analytical framework, together with the generation of a more granular geo-spatial dataset at the individual household level. Our work has, we believe, made progress on this valuation and allocation exercise. However, further progress is clearly needed to move BISs beyond their “infancy”, as noted by [29].

However, why should we care about improving BISs? As [100] has argued, the main factor that drives economic policy choices is the way in which these policies affect the distribution of income; that is, who gains and who loses as a result of the policy change. These are the types of considerations that are decisive at least in democratic societies because it is the distributional effects of policies that determine how people vote and therefore determine how their elected representatives vote. Indeed, it is through fiscal incidence analyses, both BISs and TISs, that policymakers are able to determine these distributional effects. More accurate analyses will enable policymakers to better determine who are the ultimate beneficiaries of government policies and to better design these policies to target those individuals who are most in need of them. Providing more accurate estimates of the distributional effects of government programs is therefore a crucial, perhaps a decisive, factor in maintaining the political sustainability of government policies. As noted earlier, policies whose benefits are widely distributed are more likely to generate sustainable political support. In contrast, policies that are seen as benefitting mainly either higher-income individuals or individuals who are politically well-connected are less likely to maintain similar support. Regardless of this, the ability to provide more accurate distributional estimates requires the ability to conduct more complete fiscal incidence analyses. To date, benefit incidence studies especially have often fallen far short of this standard. We hope that the methods discussed and applied in this paper will help advance these studies.

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