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Rising Incomes, Transport Demand, and Sector Decarbonization

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Abstract

As income increases, people become more mobile and spend more on carbon-intensive transport goods and services. This paper estimates income elasticities of transport consumption using household survey data for 18 countries, which are then used to simulate transport carbon footprint and carbon inequality by 2035. It first shows that in low- and middle-income countries (i) many households mostly walk and do not use transport services, (ii) income elasticity of private transport expenditure is high, and (iii) many households do not own a car. Both results suggest a future steep growth of emissions as incomes expand. Using estimates of income elasticities of vehicle ownership and vehicle use, the paper shows that carbon footprint will increase on average by 52 percent for these countries as incomes reach their 2035 levels. Finally, it decomposes carbon dioxide emissions along the within-country income distribution. Car ownership and carbon dioxide emissions are highly concentrated at the top. By 2035, carbon inequality will increase in some countries but decrease in others. Such results can be used for modeling future distributional implications of climate and energy policies.

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Rising Incomes, Transport Demand, and Sector Decarbonization

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1 Introduction

Economic development is associated with higher transport mobility. Households get richer and transition from walking to using public transport or buying a private vehicle. Consumption habits also change, and cars are increasingly used to drive around in sprawling cities. However, transport currently accounts for a quarter of energy-related carbon emissions and ranks among the fastest growing sources of such emissions (Sims, 2014; IEA, 2012). In addition, carbon emissions are unequally distributed not only between countries but also within countries (Chancel, 2021). This paper first quantifies how transport consumption, and its composition, changes as incomes rise across and within countries. It then simulates changes in carbon footprint and carbon inequalities for 18 low- and middle-income countries as income reach their 2035 levels. Such estimates can be used to assess the future distributional impacts of climate and energy policies.

The literature has shown that household demand for transport varies significantly across income levels. In high-income countries, studies using survey micro-data provide scattered evidence that direct transport-related energy consumption is less than proportional to income (Caron and Fally, 2022). Evidence from low- and middle-income countries is more limited. Studies focusing on the purchase of energy-intensive durable goods however, tend to find clear income effects towards the middle of the income distribution, suggesting significant future increases in energy demand, and carbon emissions, as large populations are just beginning to purchase energy-intensive goods (Gertler et al., 2016).

In this paper, we show how standard household surveys can be used to understand how rising incomes will affect transport consumption and the resulting transport carbon footprints and inequalities. Similar works have mostly relied on cross-country data or focused on one country, often an OECD country. However, carbon emission are expected to grow the most in non-OECD countries, for which consistent cross-country data or transportation household surveys are difficult to find. In addition, recent works have shown the benefits of using household-level data. Gertler et al. (2016) use household surveys to document motivating evidence of a nonlinear relationship between income and both asset ownership and energy use at the individual and municipality levels. Household survey data can also be used to document the distribution of transport expenditure shares within countries, which is key for the political economy of climate policies such as carbon pricing.

We identify several extensive and intensive margins of interest to quantify the impacts of rising incomes on transport consumption that are relevant for low- and middle-income countries. In low-income countries, the share of households not consuming transport goods and services remains high. The lack of access to and affordability of such goods and services limits mobility and access to economic opportunities. As their income increases, households spend more on transport and can then choose between public and/or private transport options. While private transport might be more efficient, it is also more carbon-intensive than public transport. In most countries, car ownership rates are very low. We therefore explore the determinants of vehicle ownership as well as vehicle use. The increase in first-time transport users and the extent to which the demand for private transport through vehicle ownership and use increases faster than the demand for public transport services will have different impacts on changes in carbon emission and inequality.

The paper is organized in three parts. First we present a series of stylized facts between incomes and the different margins of consumption of transport goods and services. We then use LSMS survey micro-data for 18 countries to estimate household Engel-curve expenditure elasticities. We finally use these estimates to simulate changes in transport consumption and the resulting changes in transport carbon footprint and carbon inequality in a business-as-usual scenario as incomes rise to their 2035 levels.

Main results We start by documenting the relationship between income and transport consumption across countries with a series of new stylized facts. As countries get richer, (1) more households choose to consume transport goods and services, (2) households spend an increasing share of their expenditure on transport, increasingly for private transport, and (3) car ownership as well as car use increase. We document the extent to which transport consumption significantly varies within countries across income groups. As households get richer, they spend more on transport. Rural households spend relatively less than urban households, except in high-income countries.

We then use LSMS household surveys for 18 countries to identify the main determinants of household consumption of transport goods and services and estimate elasticities of transport expenditures. We use a Zero-Inflated Poisson model given the large number of zeros expenditure and compare its results with a Poisson-Pseudo Maximum Likelihood model. Our results suggest that total expenditures per capita are a main determinant of transport expenditures. We find that on average, as per capita expenditure increases by 10%, transport expenditures increase by 17% for all transport, by 10% for transport services, and by 20% for private transport. These findings imply that private transport is a luxury good whereas public transport is a normal good. We also document disparities between and within countries, for which more work needs to be done to understand how geographic, social, and cultural differences affect transport choices. Given that most of the increase in carbon emission in low- and middle income countries is expected from first-time acquisition of motor vehicles, we estimate an ordered logistic regression using vehicle ownership data at the household level. In line with the transport literature, we identify a non-linear relationship between the probability of having a car and income. We finally explore the relationship between income and car use by using a panel of country-level data on traveled distance per car. Standard household surveys do not include questions on traveled distance at the household level.

Turning to the last part of the paper, we simulate the implications of rising incomes on transport carbon footprints and carbon inequalities. We focus on vehicle ownership and use as the main factors explaining changes in carbon footprints and inequalities for low- and middle-income countries. First-time purchasers of carbon-intensive goods will have important implications for macro-level trends in energy use (Gertler et al., 2016). For instance, vehicle ownership in urban China has risen at almost 40 percent per year between 2000 and 2010, helping fuel China's rapid growth in oil consumption (National Bureau of Statistics 2001, 2011).[1] The projections are based on the relationship between vehicle ownership and utilization that is backwards looking and do not account for future changes in the emissions intensity of transportation (electric vehicles and improved efficiency of combustion engines). While such effects will have large impacts in higher-income countries, they will remain smaller in low-income countries.[2] The simulations are done in three steps. First, we use our previous analysis to simulate how changes in income will affect car ownership and use. For our LSMS sample of 18 countries, we find that, on average, car ownership will almost double and vehicle use increase by more than 57% as incomes reach their 2035 levels. Second, we use additional data to simulate how change in car ownership and use affect carbon footprints. By 2035, we find that transport carbon emissions will increase on average by 52% in the 18 countries from our LSMS sample. Given that this effect is not linear across the income distribution, we complement our results by decomposing carbon emissions across expenditure quintiles. We show that the distribution of emissions across income groups is highly concentrated among the richest households. By 2035, carbon emissions concentration increases about twice as much for the bottom 80% than the top 20%. Within-country carbon inequality is expected to slightly decrease for the whole sample of countries, increase in some countries, but decrease in others. However, the top 20% will remain by far the main contributor to carbon emissions.

Literature review This paper is related to several strands of literature. It first complements the many studies that have analyzed the determinants of household transport expenditures. Most papers have focused their research on the impacts of change in fuel prices and on transport mobility for poor households (Ferdous et al., 2010). This literature can be classified into three categories: (i) works that describe the trend and composition of household transport spending (see e.g., Kauppila, 2011; Venter, 2011; Nie et al., 2016; Anowar et al., 2018), (ii) works that investigate the determinants of transport demand (see e.g., Gandelman et al., 2019), and (iii) works that analyze household transport spending jointly with other types of expenditures (see e.g., Choo et al., 2007). Most studies show that overall, the share of household transport expenditure over total expenditure varies from 10% to 20%, and that private transport spending represents the main component of transport expenditures with a share up to 80% in Australia or 85% in Canada. Furthermore, there are significant differences in transport shares between rich and poor households in low- and middle-income countries, especially in Africa (see e.g., Olvera

[1] More detailed mobility surveys would be needed to look at the environmental impacts of rising income on the substitution between public transport services and private transport.

[2] More work would need to be done to assess the size of the reduction in emissions intensity of transportation in low- and middle-income countries to improve the simulations.

et al., 2008). We complement these papers by providing consistent stylized facts on transport expenditures and its composition across and within countries for most countries in the world.

Second it provides estimates of Engel curves that have been widely used including in the assessment of policies related to taxation, housing, trade, but relatively less for transport. We estimate transport expenditures as a linear-quadratic function of total expenditures and other controls. Vehicle purchase is a main part of household expenditure, for which we also document an S-shaped relationship between income and durable asset ownership. Gertler et al. (2016) have rationalized the non-linearity of asset purchase in developing countries because of the presence of credit constraints. They show, in the context of rural Mexico, above a certain threshold increases in income are much more likely to lead to asset purchases. In terms of identification of the elasticity estimates, there are many unobservables that affect both total expenditures and transport expenditures that might bias the Engel curve estimates. AIDS/QAIDS type of models that overcome this problem cannot be used as price data are not available in standard household surveys. Additional works have focused on non-unitary (bargaining and collective) models to include intra-household consumption patterns and inequality (Chiappori and Meghir, 2015; Dunbar et al., 2013; Chavas et al., 2018) and on the identification of potentially confounding sources of heterogeneity in standard household Engel curve estimations due to intra-household interactions (Vreyer et al., 2020). We use standard household-level cross-sectional surveys and therefore cannot identify that effect. However, Vreyer et al. (2020) find that the null hypothesis that the household-level estimation of the Engel curves gives the same parameter estimates as one would obtain by consistent aggregation of the individual-level Engel curves for household members cannot be rejected for transport. This can be explained by the fact that vehicle purchases, a large part of transport expenditures, are common goods for the household.

Among the studies that examine the determinants of transport demand, Gandelman et al. (2019) show that incomes, gender, and age explained the level of household transport expenditures in Latin America and the Caribbean (LAC). The authors use income and expenditure surveys and find that transport expenditures increase with income. In particular, the income elasticity of public transport is lower than one while the income elasticity of private transport is greater than one. We complement this paper by doing a similar exercise for a different set of countries and improve their empirical strategy by using a ZIP regression model which performs better given the large number of zero observations. In the same vein, Graham and Glaister (2002) demonstrate that the demand of owning a car depends strongly on income with an income elasticity for fuel demand that falls in the range of 1.1 to 1.3. In another study, Thakuriah and Liao (2006) use consumer expenditure survey data to examine the relationship between transport expenditures and income in the United States. They found that transport expenditures and income belong to a virtuous circle. Indeed, they argue that increase income implies an increase of transport expenditures and vice-versa. Moreover, Thakuriah and Liao (2005) use consumer expenditure survey data to examine vehicle ownership in the United States. Using a

Tobit specification to deal with the zero-expenditure problem, they find that households' socio-economic characteristics and geographic region of residence drive their decisions to own or not a vehicle.

Turning now to studies that examine household transport expenditure along with other household expenditures, Sanchez et al. (2006) investigate the choice working households in the United States make between housing and transport expenditures. They use cluster analysis to show that these two types of spending must be analyzed conjointly. In a later study, Ferdous et al. (2010) indicate that households in the United States allocate their transport expenditures according to their socio-demographic characteristics. For instance, urban households spend a higher proportion of their income on housing and public transportation. We complement this first strand of related literature by providing stylized facts on transport expenditures at the household level based on various data sources from a heterogeneous set of countries. Transport-related questions, except for fuel consumption and asset ownership, have been difficult to harmonize across countries (Lebrand and Yin, 2022). We therefore harmonized expenditures from LSMS surveys for as many countries as possible and draw additional insights from larger harmonized survey efforts available at the country level.

Second, this paper is linked to the literature analyzing the relationship between household transport choices, energy demand, and pollution. One important margin to understand the impact of rising incomes on carbon footprint in low- and middle-income countries is the first-time acquisition of carbon-intensive vehicle by households. The growth in energy demand among first-time purchasers is likely to have important implications for macro-level trends in energy use and carbon emissions. Gertler et al. (2016) analyze household decisions to acquire energy-using assets, focusing on the role of rising incomes in the developing world, and show that non-linearities dues to credit constraints will have large impacts on energy use in developing countries. Among these studies, Dai et al. (2012) use household expenditure data in China from 1985 to 2009 to investigate how household consumption expenditure change with rises in income and infer the impacts on carbon emissions. As income rises, the authors find that households spend more on transport and energy-related products, leading to a drastic increase in carbon emissions. To reduce carbon emissions, they suggest a shift of household expenditure from material and transport products to service-oriented goods. In the same vein, Wang et al. (2016) use the social accounting matrix of China to investigate how household expenditure affects carbon emissions through income distribution in rural and urban areas. They find that carbon emissions increase with income levels for urban and rural households. They report that rural households spend a large share of their income on carbon-intensive expenditures like transport. From another perspective, some studies focus on the relationship between vehicle ownership and greenhouse gas emissions. For instance, Vasic and Weilenmann (2006) propose a comparison between the emissions from motorcycles and cars. The authors mention that motorcycles emit less carbon dioxide than cars since they are lighter and less fuel-consuming. We complement these papers by documenting the main extensive and intensive margins of transport consumption that matter for predicting the increase in carbon emissions in low- and middle-income countries and simulate changes in carbon footprints as well as within-country carbon inequality for 18 low- and middle-income countries.

The remainder of this paper is organized as follows: Section 2 presents data sources. Section 3 presents a series of stylized facts between income and the margins of transport consumption. Section 4 presents findings on income as a main determinant of transport consumption. Section 5 presents the results of the simulations of rising incomes and changes in transport carbon footprint and inequality. Section 6 concludes.

2 Data

This paper relies on times series of country-level data to provide stylized facts across countries as well as micro-level data from household surveys to provide in depth analysis of the determinants of transport demand (Table 1).

Table 1: Summary of data sources and main uses

Source	**Coverage**	**Aggregation**	**Main use**
	Household survey data		
Global consumption database	105 countries between 2000 and 2018	Averages at the quintile/urban levels	Global stylized facts
LSMS	18 countries after 2010	Raw data - Household level	Regressions for transport expenditures and vehicle ownership
World Bank SSAPOV	Sub-Saharan Africa	Country level averages	Global stylized facts
	National data		
International Road Federation	Unbalanced panel for 194 countries	Country level	Global stylized facts and Simulations
World Bank WDI GDP	Panel for all countries	Country level	Simulations
CEPII GDP projections	Panel for all countries	Country level	Simulations

2.1 Household survey data

We collect household information on transport expenditures and vehicle ownership from different sources.

Global consumption database The Global Consumption Database is a one-stop data source on household consumption patterns in developing countries, provided by the World Bank's Development Data Group. It draws on a diverse set of household consumption or expenditure surveys covering various topics, including transport. This paper uses the most up-to-date harmonized cross-section consumption data covering 105 countries between 2000 and 2018. Data is reported for a year between 2010 and 2015 for 5 countries and after 2015 for 68 countries. These countries are divided into four income groups: 24 are in the High-income group, 27 are in the Upper middle-income group, 34 are in the lower-middle-income group, and 20 countries are in the Low-income group. Expenditures are disaggregated by expenditure quintiles within each country and between urban and rural locations.

Transport expenditures are classified into three subcategories: non-durable private transport, durable private transport, and transport services. Non-durable private transport expenditures include fuels and lubricants for personal transport equipment, maintenance and repair of personal transport equipment, and other services linked to personal transport equipment. Durable private transport expenditures include durable good purchases like cars, motorcycles, bicycles, and animal-drawn vehicles. Transport services expenditures include: passenger transport by railway, passenger transport by road, passenger transport by air, passenger transport by sea and inland waterway, combined passenger transport, and other purchase transport services. Total transport expenditures are the sum of both private transport types of expenditures and transport services expenditures.

LSMS household surveys. The Living Standards Measurement Study (LSMS) is a household survey program by the World Bank's Development Data Group that provides technical assistance to national statistical offices in the design and implementation of multi-topic household surveys. This paper uses the latest LSMS surveys conducted in 18 countries from 2010 to 2018 (Table 2).[3] Most of the countries are from Sub-Saharan Africa, but there are also 3 countries from the South Asia region, one country from Europe and Central Asia region, one country from East Asia Pacific region, one country from Latin America and the Caribbean region, and 1 country from the Middle East and North Africa region. In terms of income groups: 10 countries are in the low-income group, 6 countries are in the lower middle-income group, and two countries are in the upper middle-income group.

The typical LSMS household survey contains questions on expenditures on private transport and transport services during recall periods. The questions on expenditures ask whether the households purchased any vehicles or paid for transport-related goods or services during the following periods of time: i) 7 days, ii) 1 month, iii) 3 months, iv) 6 months, and v) 1 year, and how much money was spent. Usually, short recall periods are used for transport expenditure on nondurables, such as public transport fares, fuels and lubricants, and maintenance and repairs, while the longer periods are used for transport expenditure on durables, such as purchases of vehicles, spare parts, and accessories.

Other household characteristics contained in LSMS surveys are used in the reduced-form regression part. Information on the total amount of expenditure, the size of the household and

[3]These surveys mainly fall into two categories; 10 of the 18 country surveys are from the LSMS collection included in the World Bank Microdata Library. The other 8 country surveys are from other multi-topic household surveys labelled as "LSMS-tagged" surveys.

the socio-demographic attributes of the head of household (age, education, marital status) are used.

LSMS household surveys also include information on vehicle ownership. Questions on vehicle ownership are included in the module of durable goods or household assets. The set of questions typically ask respondents whether their household own a list of vehicles (for example, car, motorcycle, minibus, bicycle, boat, animal-drawn cart), the number of vehicles they own, date of acquisition, purchase price, and estimated current resale price. However, the list of vehicles and the sophistication of questions vary by country, which means that some questionnaires do not collect sufficient information to estimate the annual use value of vehicles, calculated based on the purchase and resell prices, and the date of acquisition.[4]

Table 2: LSMS surveys countries

Collection	Country	Region	Income group	Survey name	Survey year
LSMS Surveys	Burkina Faso	AFR	Low income	Continuous Multisectoral Survey	2014
	Ethiopia	AFR	Low income	Socioeconomic Survey	2015/16
	Iraq	MENA	Upper middle income	Household Socioeconomic Survey	2012
	Malawi	AFR	Low income	Integrated Agricultural Survey	2016/17
	Mali	AFR	Low income	Living Standards Survey	2014/15
	Nepal	SAR	Low income	National Survey on Household Living Conditions and Agriculture	2010/11
	Niger	AFR	Low income	General Household Survey	2014/15
	Nigeria	AFR	Low middle income	National Panel Survey	2015/16
	Tanzania	AFR	Low income	Living Conditions Survey	2014/15
	Uganda	AFR	Low income	Cameroonian Household Survey (ECAM-IV)	2015/16
Other multi-topic surveys (LSMS-tagged)	Afghanistan	SAR	Low income	Integrated Household Survey	2016/17
	Cameroon	AFR	Low middle income	Household Socioeconomic Survey	2014
	Kyrgyz Republic	ECA	Low middle income	National Household Survey on Living Standards Measurement (EMNV)	2013
	Mongolia	EAP	Low middle income	Social and Living Standards Measurement Survey	2016
	Nicaragua	LAC	Low middle income	Integrated Household Survey	2014
	Pakistan	SAR	Low middle income	Living Conditions Survey	2013/14
	Sierra Leone	AFR	Low income	Integrated Agricultural Survey	2018
	South Africa	AFR	Upper middle income	Living Conditions Survey	2014/15

World Bank database SSAPOV The Sub-Saharan Statistical Development team harmonized the existing household surveys in the Sub-Saharan Africa region by extracting about 200 variables and unifying the definitions and variables names. SSAPOV contains the harmonized information on ownership of vehicles for 33 countries. We use data about ownership of cars, motorcycles, and bicycles. Unfortunately no other variable linked to transport expenditures has been harmonized in this database

2.2 Country-level datasets

International Road Federation (IRF). We use vehicle ownership data included in the World Road Statistics database produced by IRF. These data are panel data covering 194 countries from 2000 to 2017. More specifically, we use data on vehicle in use including: Passengers cars, Buses and Motor coaches, Vans, Pick-ups, Lorries, Road Tractors, and Motorcycles.

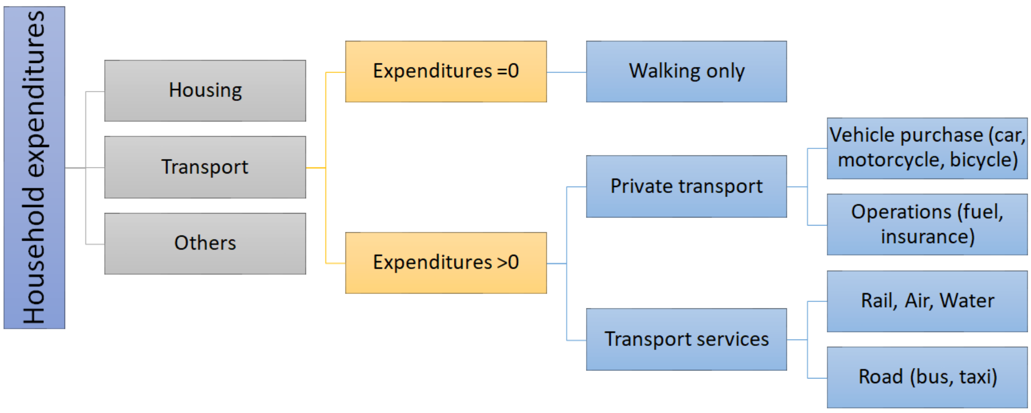
[4]The standard LSMS household survey questionnaires in Nepal even involve a question on whether the vehicle was purchased by the household or received as a gift, payment for services, or inheritance.

Others Several country-level datasets on carbon emissions and GDP projections are used to complement household survey data. Data on carbon emissions from transport come from the World Bank. These data cover 195 countries and span from 2000 to 2017. We use GDP data from the World bank development indicators database. GDP growth projections are reported using growth scenarios for 147 countries to 2050 produced by CEPII (Fouré et al., 2012).

2.3 Categories of transport expenditures

Items of transport expenditures are categorized according to the following Figure 1. Transport is one among other consumption items, such as food or housing. Private transport includes all expenditures related to the use of a private vehicle. Transport services include all expenditures using shared and public transportation services such as train or buses. Total transport expenditure is the sum of private transport and transport services expenditures.

Figure 1: Categories of transport expenditure items



Global consumption database We follow the COICOP1 classification of subcategories of transport expenditure to construct our main categories. Private transport costs is divided into variable costs and purchase of durable goods. Variable costs include fuels and lubricants, maintenance and repair, and other services in respect of personal transport equipment. Purchase of durable goods include goods such as cars, motorcycles, bicycles, and animal drawn vehicles. Transport services costs include passenger transport by railway, by road, by air, by sea and inland waterway, combined passenger transport, and other purchase transport services.

LSMS Household surveys In the typical LSMS survey, information on private transport non-durables and transport services can be captured in the non-food expenditure sections with different recall periods (7 days/ 3 months/ 6 months/ 1 year), and information on private transport durables in the durable goods section.

3 Income and the margins of transport consumption: stylized facts

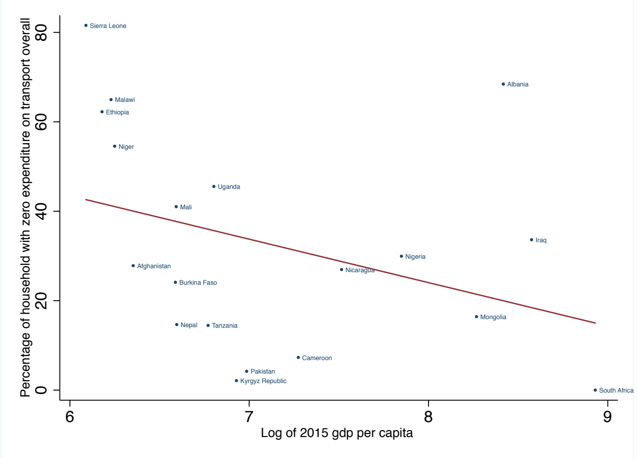
Households choose which transport modes to use and how much to spend on transport goods and services. We identify several extensive and intensive margins of interest behind transport consumption. In poorer countries, many households mostly walk and do not consume transport goods or services. The carbon footprint of such countries will therefore increase as first-time users start consuming transport goods and services. As they get richer, households then choose between public and/or private transport options and spend more on transport goods and services. While private transport might be more efficient, it is also more carbon-intensive than public transport. The total carbon footprint of private transport will depend on vehicle ownership as well as vehicle use. For each margin, this section presents a series of global stylized facts between income and transport consumption.

3.1 Income and first-time transport users

Fact 1: In poorer countries, a large share of households do not consume transport goods or services. Figure 2 uses LSMS household data to plot the average share of households not consuming transport goods or services per country against country GDP per capita. There are large differences between shares of households with zero-transport expenditures across countries. The percentage of zero-transport expenditure observations is very high in countries like Sierra Leone and Malawi (82% and 65% respectively), while it is null in South-Africa. Figure 2 shows that there is a negative correlation between the percentage of households with zero transport expenditures and country GDP per capita.[5] Poorer countries tend to have a higher share of households not spending money to increase their mobility. As countries get richer, the share of households not consuming transport goods or services decreases.

[5] The correlation coefficient is -0.35

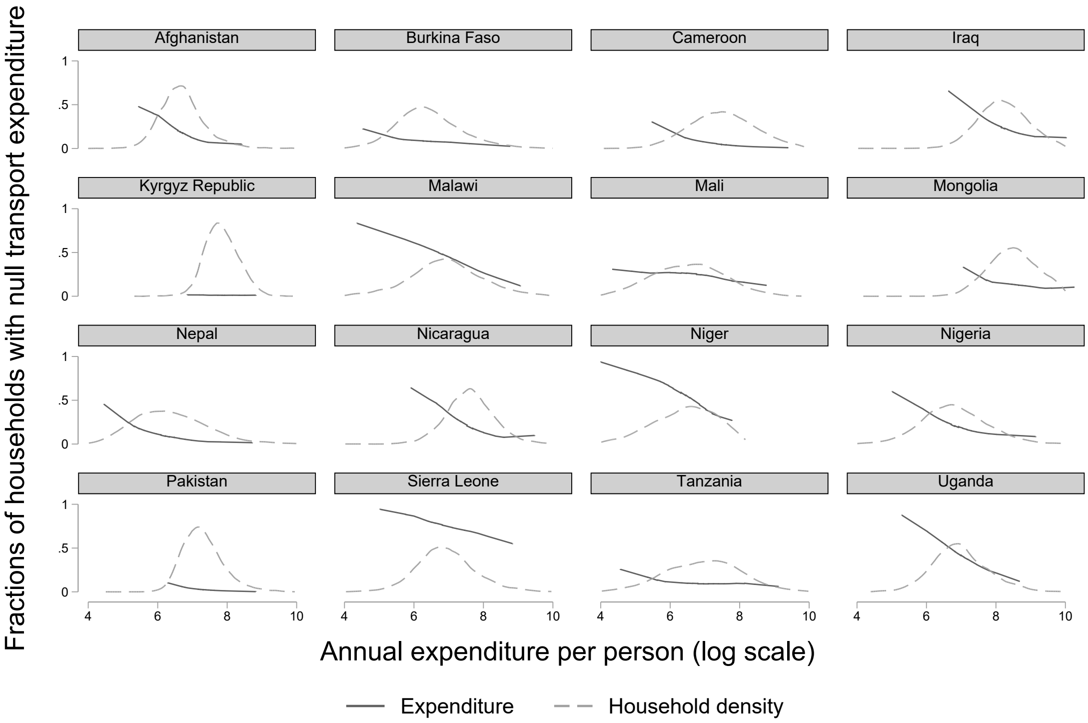
Figure 2: Zero-transport expenditures and GPD per capita



Note: Authors' calculations based on LSMS surveys.

Figure 3 uses LSMS household data to plot the share of households with null transport expenditures against household expenditures per capita within country. The dashed lines show the density of households by expenditure level. As households get richer, they increasingly start spending on transport and the share of households with null expenditure decreases. Differences across countries depend on income levels but also exogenous factors such as the weather and geography, the distribution of population and economic activities, and the supply of transport goods and services. The LSMS sample covers countries with different levels of GDP per capita. As a result, for some countries including Malawi, Niger, Sierra Leone or Uganda, a substantial share of households has yet to move through the income levels associated with non-zero transport consumption.

Figure 3: Share of households with zero transport expenditure



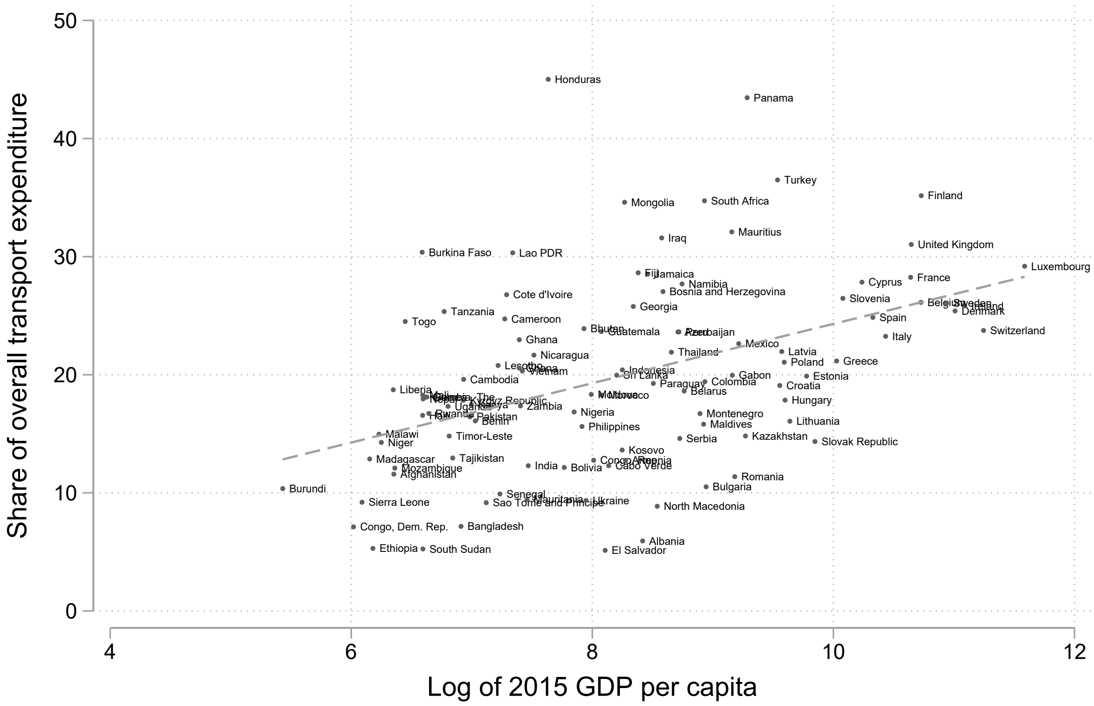
Note: The graphs report the smoothed relation using the lowess function between per-capita expenditure and the share of households with zero transport expenditure using LSMS surveys.

3.2 Income and transport expenditures

Fact 2: Households spend relatively more on transport goods and services as countries get richer. Figure 4 uses data from the Word Bank Global Consumption Database to plot the share of overall transport expenditures in total expenditures against the log of GDP per capita for most countries in the world. Shares of transport expenditures vary across countries, going from 3% in Tanzania to 22% in Honduras. The average share of transport expenditures in total household consumption is significantly correlated with GDP per capita.[6]

[6]The correlation coefficient is 60%.

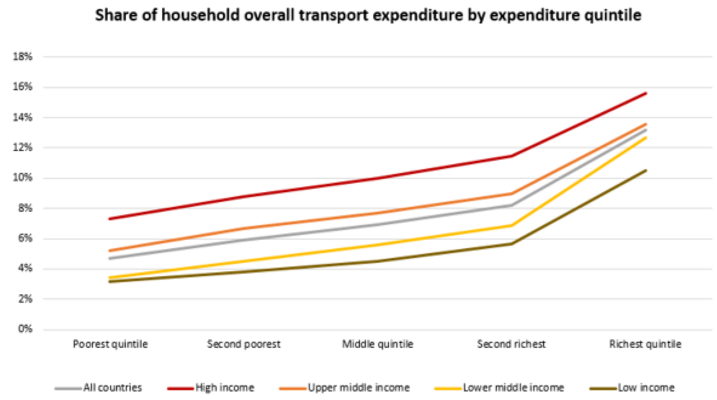
Figure 4: Share of overall transport expenditure and GDP per capita



Note: Authors' calculations using the updated Word Bank Global Consumption Database.

Fact 3: Within countries, richer households spend more on transport than poorer households Figure 5 uses data from the Word Bank Global Consumption Database to plot the share of overall transport expenditures in total expenditures per quintile of total expenditures within country. Richer households spend relatively more on transport and the difference between the richest and the poorest quintiles is the highest in poorer countries. On average, households in the richest quintile spend 15% of their expenditures on transport, while households in the poorest quintile spend 5% of their expenditures on transport. These shares vary across income groups. The share of transport expenditures for households in the richest quintile compared to households in the poorest quintile is twice larger in high-income countries, almost 3 times larger in upper-middle income countries, and more than 3 times larger for lower-middle and low-income countries.

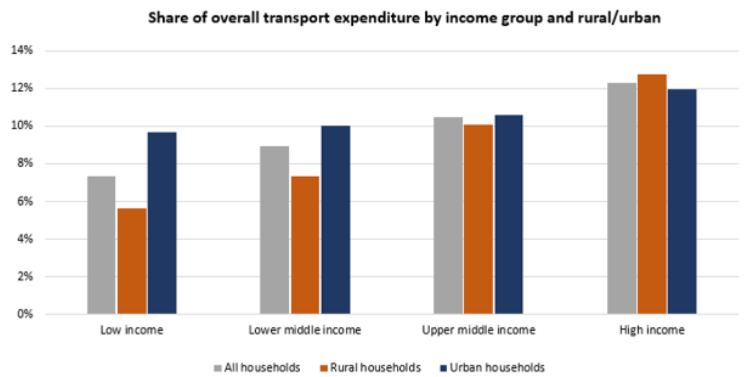
Figure 5: Transport expenditures by expenditure quintile



Note: Authors' calculations using the updated Word Bank Global Consumption Database.

Fact 4: Rural households spend relatively less than urban households, except for high-income countries Figure 6 uses data from the Word Bank Global Consumption Database to plot the average share of overall transport expenditures in total expenditures for rural and urban households. Rural households spend on average less than urban households, except in high-income countries. The gap is the largest for poorer countries, and diminishes as countries get richer. Urban households spend on average twice more than rural households in low-income countries, 40% more in lower-middle income countries, and a similar share for other income groups. The extent to which income levels or living in a rural/urban location impact transport expenditures will be determined in the next section.

Figure 6: Transport expenditures by income group and rural/urban



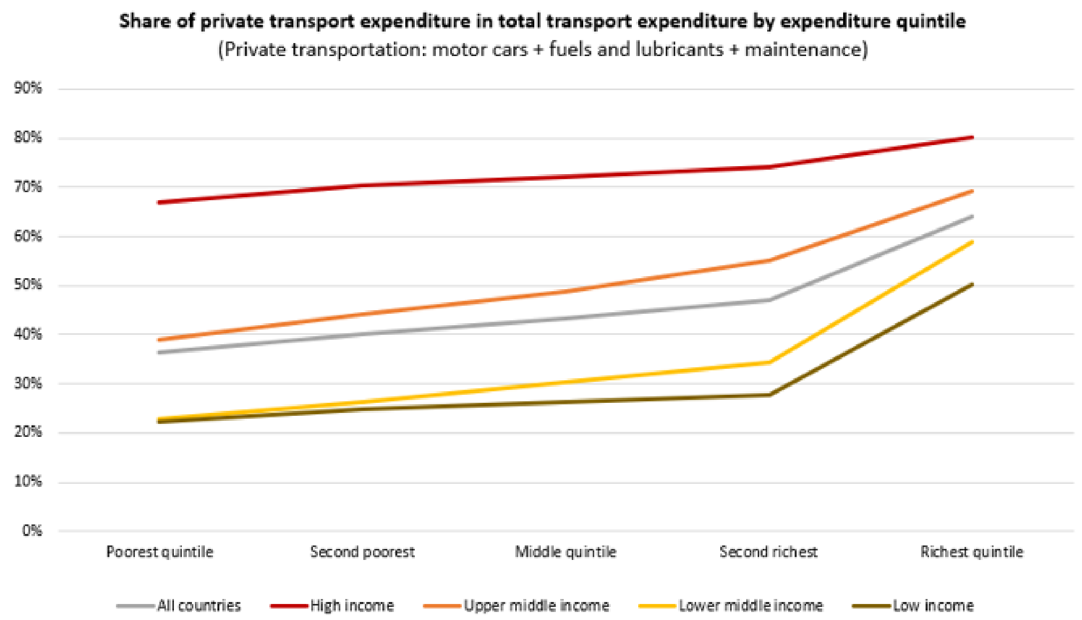
Note: Authors' calculations using the updated Word Bank Global Consumption Database.

3.3 Income and the composition of transport consumption

Using public transportation has a lower carbon footprint than using private cars and is often more affordable. While poorer households cannot afford a private car and only use public transportation, richer households can choose between public and private transportation.

Fact 5: Richer households spend relatively more on private transport than on transport services Figure 7 uses data from the Word Bank Global Consumption Database to plot the share of private transport expenditures in overall transport expenditures per quintile of total household expenditures within country. Incomes affect the composition of transport expenditures as households substitute between private transport and transport services in poorer countries. Households in richer countries and richer households in other income groups spend relatively much more on private transportation, which includes expenditures for cars, fuel, and maintenance, than on transport services. Except for high-income countries, there is a large discrepancy between the shares of private transport expenditure in total transport expenditure when comparing the richest quintile with other quintiles. In low-income countries, the share of private transport goes from 20% for the poorest quintile to 50% for the richest quintile. In high-income countries, all households, independently of their quintile, spend between 70% and 80% of their transport expenditures on private transportation. This reflects the fact that only very few households can afford to own and maintain a car in poorer countries.

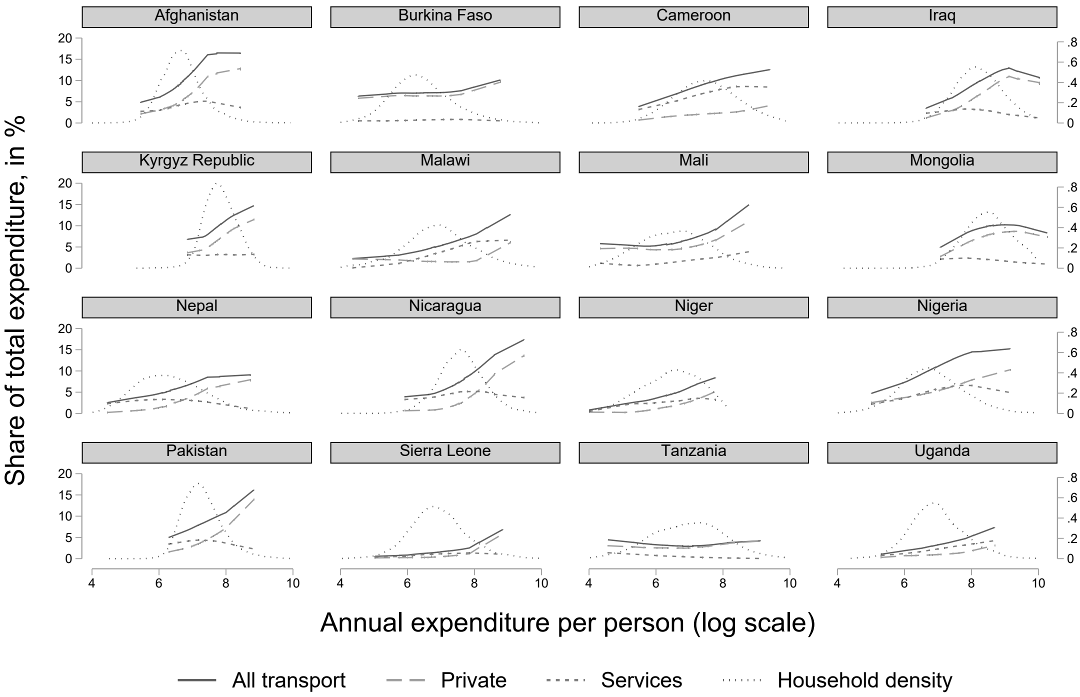
Figure 7: Share of private transport expenditure in total transport expenditure by expenditure quintile



Note: Authors' calculations using the updated Word Bank Global Consumption Database.

Figure 8 uses LSMS household data to plot the share of total transport consumption as well as the consumption of private transport vs transport services in total expenditures against household expenditures per capita. The dashed lines show the density of households by expenditure level. As households get richer, they increasingly spend on transport overall. Except for Cameroon and Uganda, most of the growth in transport expenditure share is associated with a growth in private transport expenditures. Across countries, poorest households spend mostly on transport services while the share of private transport expenditures grows as households get richer. Private transport expenditures are overall increasing in a non-linear way. Figure 8 shows that for many countries a substantial share of households still consumes mostly public transport services, and have yet to start spending on private transport goods and services, which mostly depend on asset ownership.

Figure 8: Share of transport expenditure in total expenditure for the LSMS sample of countries



Note: Authors' calculations using the LSMS surveys.

3.4 Income and private transport

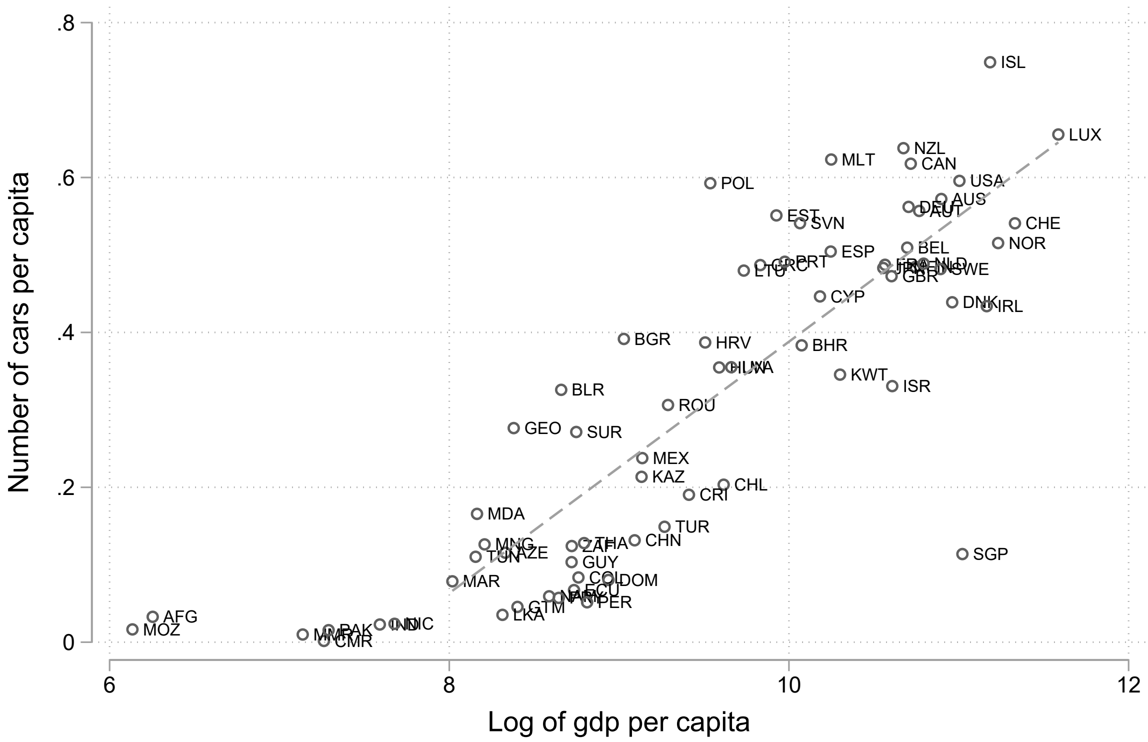
Expenditures for private transport include the acquisition, use, and maintenance of vehicles. The extent to which the consumption of private transport will affect carbon emissions depends on the number and types of vehicles and the intensity of use.

3.4.1 Income and vehicle ownership

Fact 6: As countries get richer, more households acquire cars and each household might acquire more than one car. Figure 9 uses data from the International Road Federationfor 2017 to plot the number of passenger cars per 1000 inhabitants against country GDP per capita. Except for the poorest countries, there is a log-linear relation between country income levels and car ownership.[7] Using similar data for motorcycles, we show that there is no similar relationship between motorcycle ownership and GDP per capita.

[7]The correlation coefficient between the number of passengers cars and the log of GDP per capita is 81%.

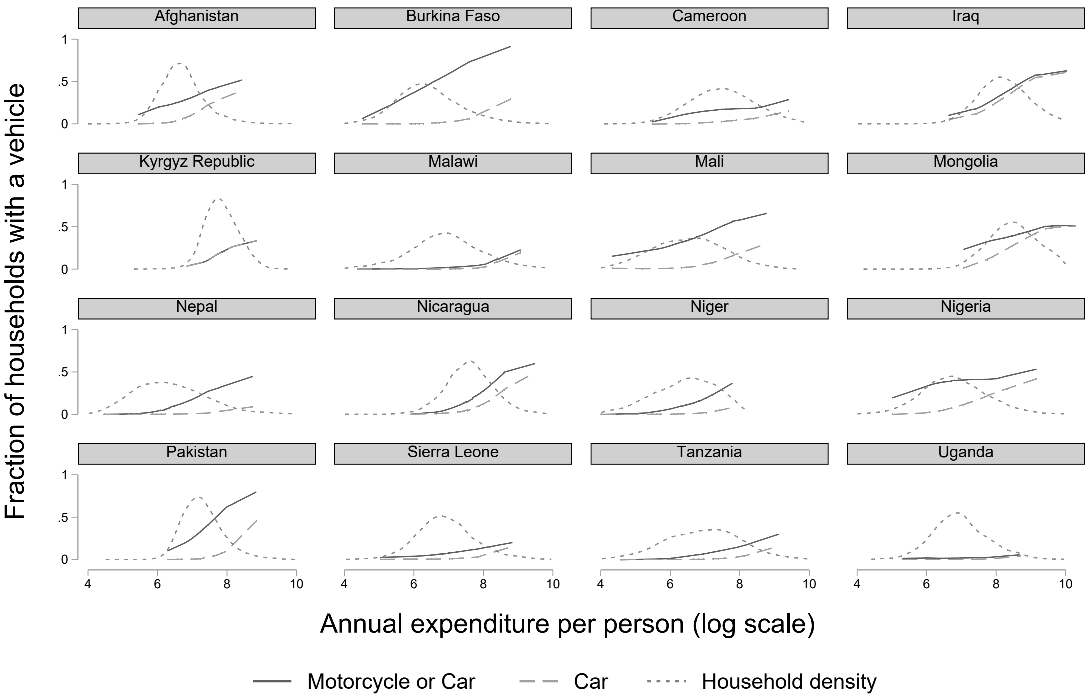
Figure 9: Passenger cars and GDP per capita



Source: IRF data for passenger car ownership. Most data points are for 2017, when missing they are replaced by the latest available year between 2014 and 2016.

Fact 7: As households get richer, they are more likely to own a car. Figure 10 uses LSMS household data to plot the fraction of households that own at least a vehicle, being a motorcycle or a car, against household expenditures per capita within country. The dashed lines show the density of households by expenditure level. As households get richer, they are more likely to own a vehicle. For Burkina Faso, Mali, Cameroon, Nigeria, and Pakistan, most of the growth in vehicle ownership comes from the acquisition of a motorcycle. For most countries in the LSMS sample, the probability to own a car is almost null for most of the population, except for the richest. The probability to own a car is increasing in a non-linear way, in line with Gertler et al. (2016) who provide evidence of a nonlinear relationship between income and asset ownership as credit-constrained households become more likely to purchase an energy-using asset only above a certain income threshold. Figure 8 shows that for many countries a large share of households do not own a vehicle, and have yet to reach the income threshold to be able to acquire a vehicle.

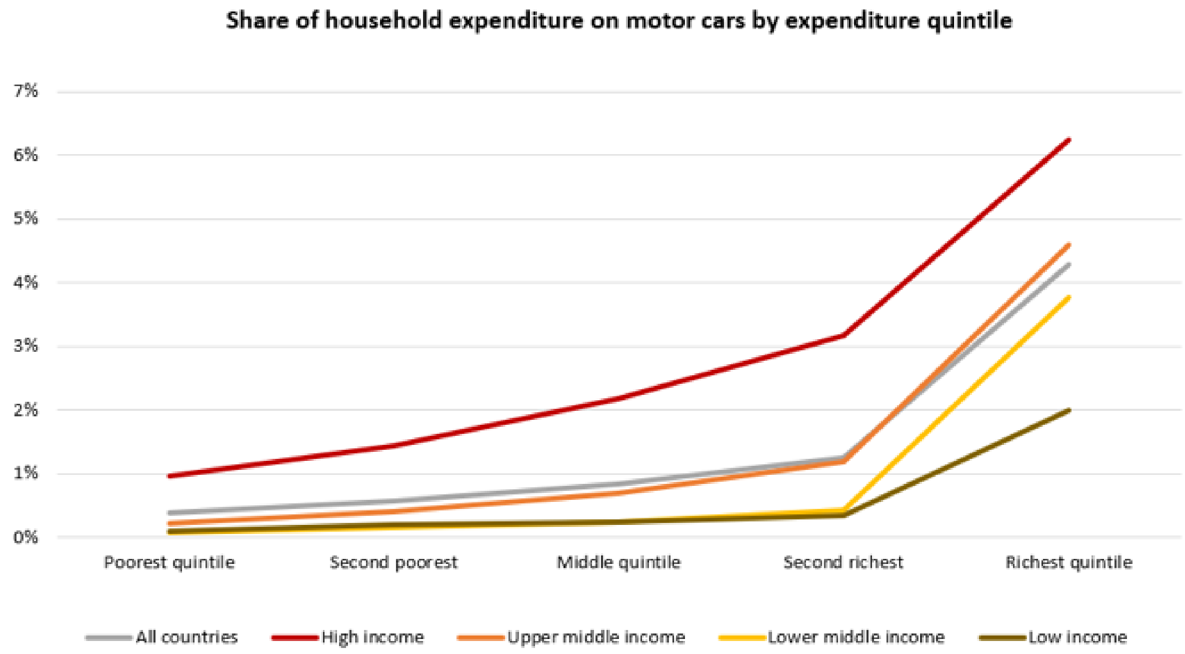
Figure 10: First-time asset buyers



Note: Authors' calculations using the LSMS surveys.

Fact 8: Within countries, households spend relatively more on cars as they get richer. Figure 11 uses data from the Word Bank Global Consumption Database to plot the average share of household expenditure on motor cars by expenditure quintile. In most countries except high-income countries, the share is negligible and only increases for the richest quintile, which reflects the concentration of private car ownership among the few richest households. The amount spent on cars depends whether households own a car but also on the number and quality of cars. Richer households tend to acquire multiple and more expensive cars.

Figure 11: Share of households' total expenditures on cars

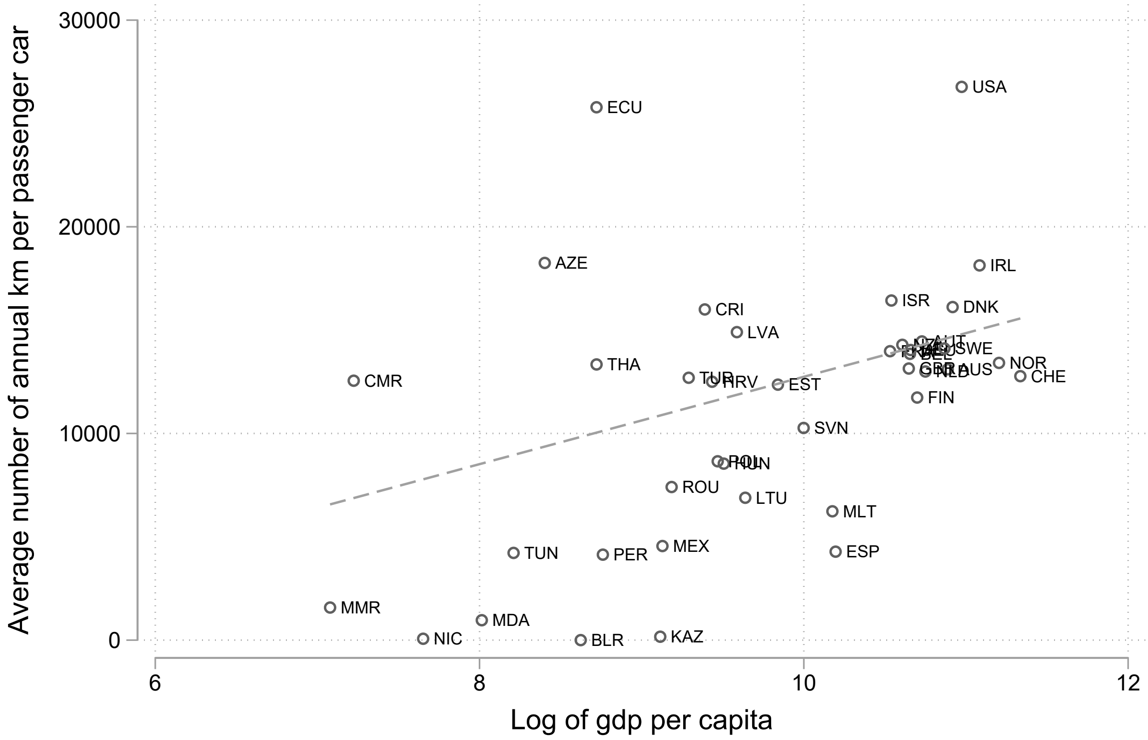


Note: Authors' calculations using the updated Word Bank Global Consumption Database.

3.4.2 Income and vehicle use

Fact 9: As countries get richer, households tend to drive more. Figure 12 uses data from the International Road Federation data over the period 2015-2017 to plot the average annual number of km per passenger car against the log of GDP per capita. There is overall a positive relation between vehicle use and GDP per capita. As incomes increase, households might use their cars more often, for longer trips, and for more purposes (commuting, access to services, holidays, etc). More work needs to be done but data on vehicle use at the household level are difficult to find outside of a few countries. Vehicle use is, however, an important margin for understanding the link between income and total carbon footprint.

Figure 12: Vehicle use per country



Source: IRF data for passenger car ownership and car-km per country. The average number of annual km per passenger car is calculated by dividing the total number of car-km per the number of passenger cars. The graph shows averages over the period 2015-2017 to limit the extent of reporting mistakes.

4 Income as a main determinant of transport consumption

As documented in the previous section, there are large differences across countries and within countries across households with different incomes. Calculating elasticities of transport demand based on cross-country averages would therefore miss the large differences in transport demand and use of carbon-intensive goods that exist within countries. This section uses household survey data to estimate transport elasticities. Harmonized survey data across countries with sufficient transport-related questions are rare. We therefore focus on 18 countries for which we use the rich collection of data from LSMS surveys. Households decide whether to consume transport goods and services, and by how much, to increase their mobility and their economic and social opportunities. We look at the role of income as a main determinant for each of the margin identified in the previous section.

4.1 Household-level estimation

In order to quantify the determinants of transport expenditures at the micro-level, we estimate the relationship between the level of transport expenditures and households' characteristics using LSMS surveys for 18 countries after 2010.

4.1.1 Data challenges

Dealing with the presence of a large number of zero-transport expenditures and including expenditures on durable goods in the total transport expenditure per household are the two main data challenges to consider before estimating the model.

Large number of zero-transport expenditures There is a substantial number of observations with zeros in all transport subcategories of private transport nondurables and transport services. A household is assumed not to spend on transport either when the answer is zero, or when a missing entry can be recorded as zero.[8]

Include private transport durables LSMS surveys contain information on private transport durable goods included in the durable goods section. Durable goods are a category of consumer goods that do not wear out quickly, and therefore do not have to be purchased frequently. Therefore, durables goods need a particular treatment. We follow the procedure from Deaton and Zaidi (2002) to calculate the annual value of transport durables using the following equation:

$$\text{Annual use value} = S_t P_t (r_t - \pi_t + \delta) \tag{4.1}$$

Where $S_t P_t$ is the current value of durables ; $r_t - \pi_t$ is the real interest rate; δ is the depreciation rate. Because of missing values and outliers, we use the median value (12 %) of countries' real interest rates for the survey year or the latest year available for all countries (Table A.2 in the Appendix). We then estimate depreciation rates for the countries for which the LSMS surveys contain information on purchase value, current resell value and age of durables using the following approximation:

$$\text{Depreciation rate} = 1 - \left(\frac{\text{Current value of the item}}{\text{Purchase value of the item}}\right)^{(\text{1/age of the item})} \tag{4.2}$$

For all countries, we use the median value (8 %) to deal with missing values and outliers (Table A.2 in Appendix).

4.1.2 The determinants of transport expenditures

We want to estimate the following specification:

$$ln\Big(y_i\Big) = \alpha + \beta f\Big(ln(\frac{x_i}{n_i})\Big) + \gamma ln(n_i) + \phi z_i + FEs + \nu_i \tag{4.3}$$

[8] The missing expenditure entries can be recoded as zeros when there is a screening question on whether the household purchased the items over a certain period or owns the durables.

with

- y_i = Per capita transport expenditure of the household i
- x_i = Total expenditure of the household i
- n_i = Household size
- z_i = A vector of other household socio-demographic characteristics, including age, gender, educational level of household head, and urban versus rural location.
- FEs a series of country or subnational fixed-effects.

Estimation strategy The existence of many observations for which the dependent variable is zero creates a problem for the use of the log linear form. Several methods have been used to deal with this problem. A first solution is to simply drop the observation with zero expenditure from the data set and estimate the log linear form by OLS. A second solution is to estimate the model using Y+1 as the dependent variable or use a Tobit estimator (Gandelman et al., 2019). However, these procedures will generally lead to inconsistent estimators of the parameters of interest.

Given the large number of zeros, we need to decide whether the zero and positive observations are generated by the same mechanism or whether the zeros are somehow different (Santos Silva et al., 2015b). When it is assumed that a single mechanism is at work the data are typically described by a single-index model such as the Tobit or by models with an exponential conditional expectation function (Santos Silva and Tenreyro, 2006). If the zeros are believed to be generated by a different process, the covariates are allowed to affect the conditional distribution in two different ways, leading to double-index models such as the two-part models, models based on Heckman's (1979) sample selection estimator, or zero inflated models. We compare the performance of two models, the Poisson pseudo-maximum-likelihood (PPML) specification that assumes that the zeros are generated by the same mechanism, and the Zero-Inflated Poisson model that assumes that the zeros are different. Compared to the PPML model, the zero-inflated regression model has the important drawback of not being invariant to the scale of the dependent variable. If expenditures are measured in dollars or hundreds of dollars, the estimates of the elasticities will change.

Santos Silva and Tenreyro (2006) propose the Poisson pseudo-maximum-likelihood method in the case of many zero observations. They show that the estimator is robust to different patterns of heteroskedasticity and provides a natural way to deal with zeros in trade data. Simulation evidence on the good performance of the PPML estimator when the data has many zeros can be found in Santos Silva and Tenreyro (2011). While expenditure data are continuous, PPML does not require the data to follow a Poisson distribution because a pseudo-maximum likelihood estimator is used. The PPML specification is given by the following:

$$y_i = exp\Big(\alpha + \beta ln\Big(\frac{x_i}{n_i}\Big) + \delta ln\Big(\frac{x_i}{n_i}\Big)^2 + \gamma ln(n_i) + \phi z_i + FEs + \nu_i\Big) \tag{4.4}$$

The other specification is the zero-inflated Poisson model (ZIP) that allows for frequent zero-valued observations. The model applies when the excess zeros are generated by a separate process from the count values and that the excess zeros can be modeled independently. This model allows for overdispersion assuming that there are two different types of individuals in the data: those who have a zero count with a probability of 1 (Always-0 group), and those who have counts predicted by the standard Poisson (Not always-0 group). The overall model allows for both the overdispersion and excess zeros that cannot be predicted by the standard Poisson model. The ZIP model therefore mixes two zero generating processes. The first process generates zeros through a logit model. The second process is governed by a Poisson distribution that generates counts, some of which may be zero. A household in the "Always-0 group" is a binary outcome that can be predicted by a logit model. The probability ϕ_i that observation i is in Always-0 group is predicted by the characteristics of observation i and can be written as:

$$\phi_i = F(\alpha + \beta^0 ln\Big(\frac{x_i}{n_i}\Big) + \delta^0 ln\Big(\frac{x_i}{n_i}\Big)^2 + \gamma^0 ln(n_i) + \phi^0 z_i + FEs + \nu_i) \tag{4.5}$$

with β^0, δ^0, γ^0, and ϕ^0 the coefficients of the first-stage logit regression. Then the probability that observation i is not in the "always-0" group becomes $1 - \phi_i$. For observations in the "Not always-0" group, their positive count outcome is predicted by the standard Poisson model.

Finally we discuss the performance of each model based on tests applied to discriminate between these two models. The usual AIC and BIC tests are based on the likelihood function and are therefore not valid if at least one of the models is estimated by pseudo maximum likelihood, as it is the case for the PPML model. Following Santos Silva et al. (2015b), we therefore compare the performance of the two models for non-negative data with many zeros using the HPC test developed by Santos Silva et al. (2015a) and the Stata module available from Santos Silva and Tenreyro (2015).

4.2 The determinants of transport expenditures and its composition

Tests Following Santos Silva et al. (2015a), we use the HPC test to choose between competing models for non-negative data with many zeros. The question is whether the zero and positive observations are generated by the same mechanism (PPML) or whether the zeros are somehow different (ZIP). The HPC test can be used to test whether or not the zero and positive observations are generated by different mechanisms. Table 3 shows the results for several sets of simulations for all transport expenditures, transport services expenditures, and private transport expenditures. For each type of expenditure, the PPML model is tested against the ZIP model, and vice-versa. The table includes the R-Squared for each model (computed as the square of the correlation between the dependent variable and the estimated conditional mean), and the p-value of the HPC test of the sample selection estimator against the other model and vice-versa.

It results that both models perform similarly when comparing the R-Squared measures. When comparing the p-values, the HPC tests reject the PPML specification for all types of expenditures, while providing no evidence of departures of the ZIP model in the direction of its competitor. In the rest of the paper, we therefore present and discuss the results of the ZIP model only. The results of the regressions using both PPML and ZIP models are available in the Appendix.

Table 3: HPC tests between PPML and ZIP models

	All Transport		Services		Private	
Ho: Model .. is valid	PPML	ZIP	PPML	ZIP	PPML	ZIP
Prob > t	0.149	0.496	0.000	1.000	0.000	0.958
R Square	.384	.387	.209	.203	.336	.343
Country FE	No		No		No	
Subnational FE	Yes		Yes		Yes	

4.3 Extensive margin: first-time users of transport goods and services

Tables 4 and 5 present the results of the estimation of the ZIP model when all observations across countries are pooled and including subnational fixed-effects and the square expenditure per capita as a variable in the regression. Table 4 reports the estimation results of the inflate logit estimation part, and Table 5 the main Poisson estimation.

Table 4: First stage of the ZIP regression for all transport, transport services and private transport.

Dependent variable: Whether transport expenditure is non-zero			
	All transport	Transport Services	Private transport
Log per cap. exp.	-0.669**	-2.698**	-0.208*
	(-6.32)	(-34.59)	(-2.35)
Square Log per cap. exp.	-0.0371**	0.143**	-0.0617**
	(-5.01)	(27.83)	(-10.54)
Age of head	0.00696**	0.00397**	0.00314**
	(12.77)	(8.65)	(6.63)
Complete secondary education	-0.152**	0.0296	-0.152**
	(-6.65)	(1.64)	(-8.81)
Log household size	-1.342**	-0.518**	-1.518**
	(-79.17)	(-38.28)	(-97.82)
Urban	0.207**	0.0157	0.301**
	(9.86)	(0.95)	(18.20)
Female	0.535**	-0.165**	1.095**
	(24.87)	(-8.89)	(51.98)
Subnational FE	Yes	Yes	Yes
N. of observations	153133	153133	147153

t statistics in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 5: Second stage of the ZIP regression for all transport, transport services and private transport.

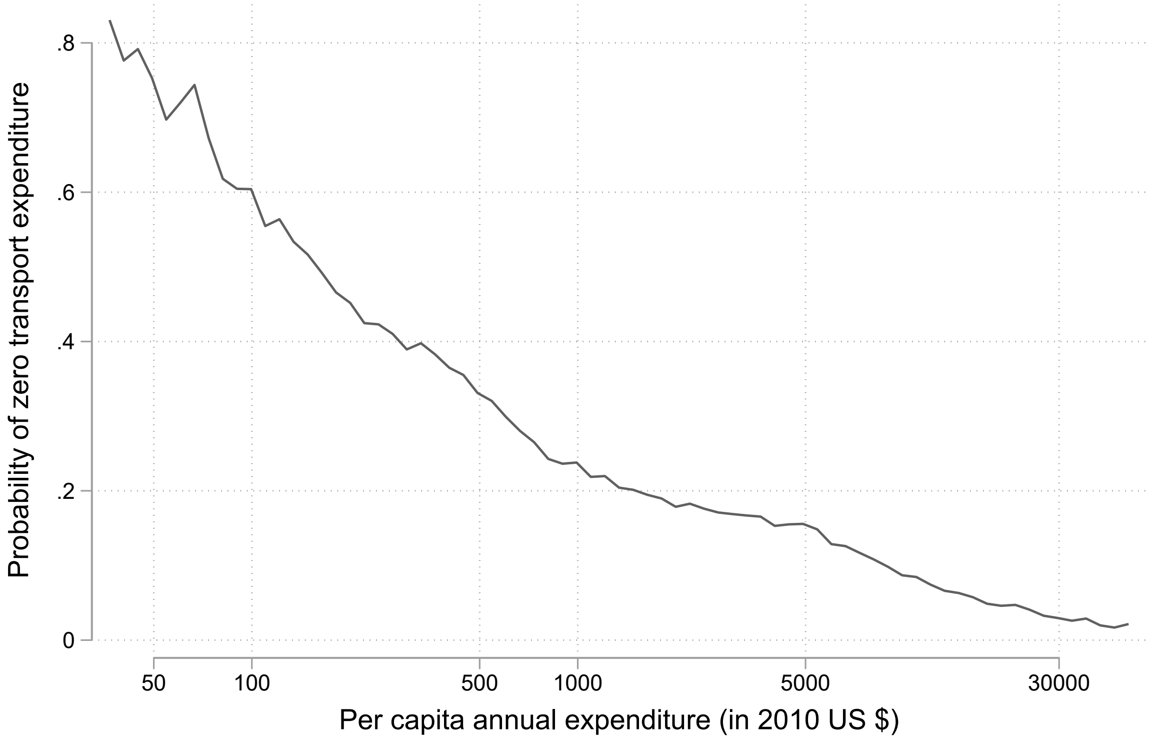
Dependent variable: Transport expenditures			
	All transport	Transport services	Private transport
Log per cap. exp.	3.054**	1.481**	3.526**
	(34.28)	(14.16)	(32.90)
Square Log per cap. exp.	-0.112**	-0.0500**	-0.141**
	(-20.64)	(-7.52)	(-21.92)
Age of head	-0.000879*	0.00000777	0.000106
	(-2.50)	(0.02)	(0.25)
Complete secondary education	0.0925**	0.0820**	0.0502**
	(8.39)	(6.32)	(3.86)
Log household size	0.0761**	-0.404**	-0.0980**
	(7.46)	(-38.52)	(-7.56)
Urban	-0.117**	-0.0481**	-0.0801**
	(-10.91)	(-3.79)	(-6.51)
Female	-0.359**	0.0157	-0.243**
	(-22.13)	(1.11)	(-10.47)
Subnational FE	Yes	Yes	Yes
N. of observations	153133	153133	147153

t statistics in parentheses, $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Note: The table reports the results of the ZIP model for the specification with square per capita expenditure and subnational FEs.

Table 4 shows that the probability of never spending on transport decreases with income, education, and household size, but increases with age of the household head, in urban locations, and for women. Figure 13 shows the average post-estimation predictions of zero expenditure per levels of per capita annual expenditure across countries. The poorest households have a probability to not spend on transport as high as 80%, while this probability decreases quickly below 20% for individuals whose annual expenditures are superior to US$1700.

Figure 13: Probability of spending zero on transport



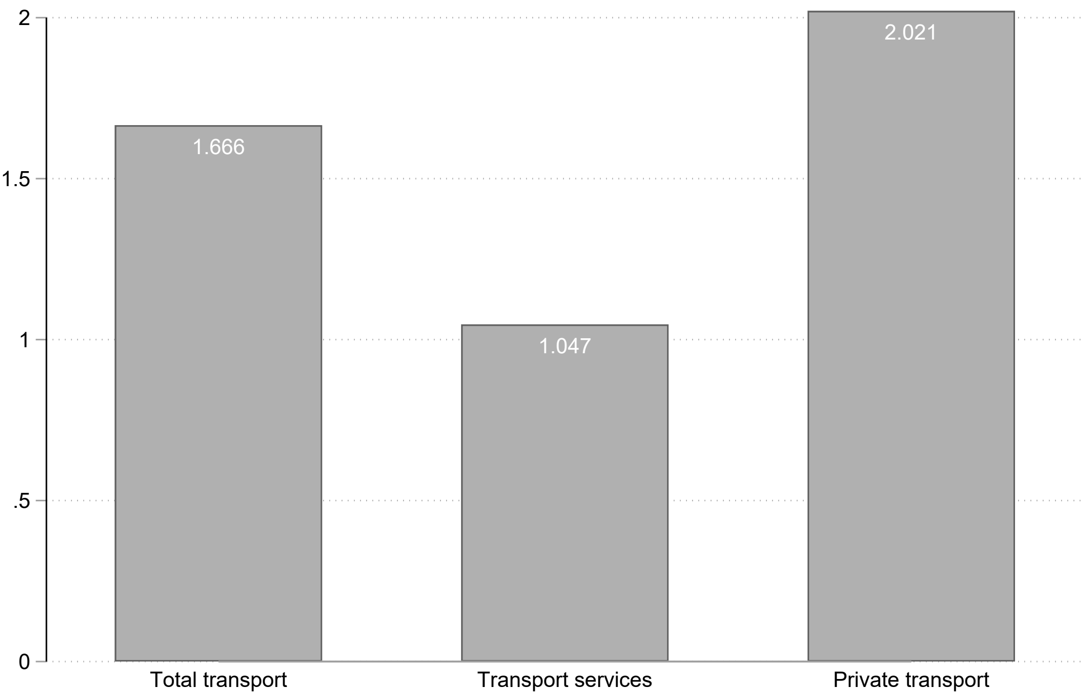
Source: Authors' calculations.

4.4 Intensive margin: transport expenditures and its composition

Main determinants of transport expenditures Table 5 reports that transport expenditures increase in income, education, and household size, but decreases with age of the household head, in urban locations, and for women. The results are similar for private transport expenditures, except for the impact of household size. Indeed there are economies of scale from buying, using and maintaining a car in larger households. Expenditures on transport services also increase in income and education, but decrease in household size and are not significantly different between men and women.

Aggregate Expenditure Elasticities Figure 14 reports the average expenditure elasticity per type of transport expenditures using the ZIP specification with square expenditures and subnational fixed effects. For comparison, Tables B.10, B.11, B.15 in the Appendix show the resulting average expenditure elasticites from PPML and ZIP specifications with different fixed-effects. The results are similar when using PPML and ZIP models. On average, as total per capita expenditure increases by 10%, transport expenditures increase by 17% for all transport, by 10% for transport services, and by 20% for private transport. Transport, especially private transport, is defined as a luxury good with an elasticity much higher than 1, while transport services is normal as its consumption level increases proportionally with total expenditure level.

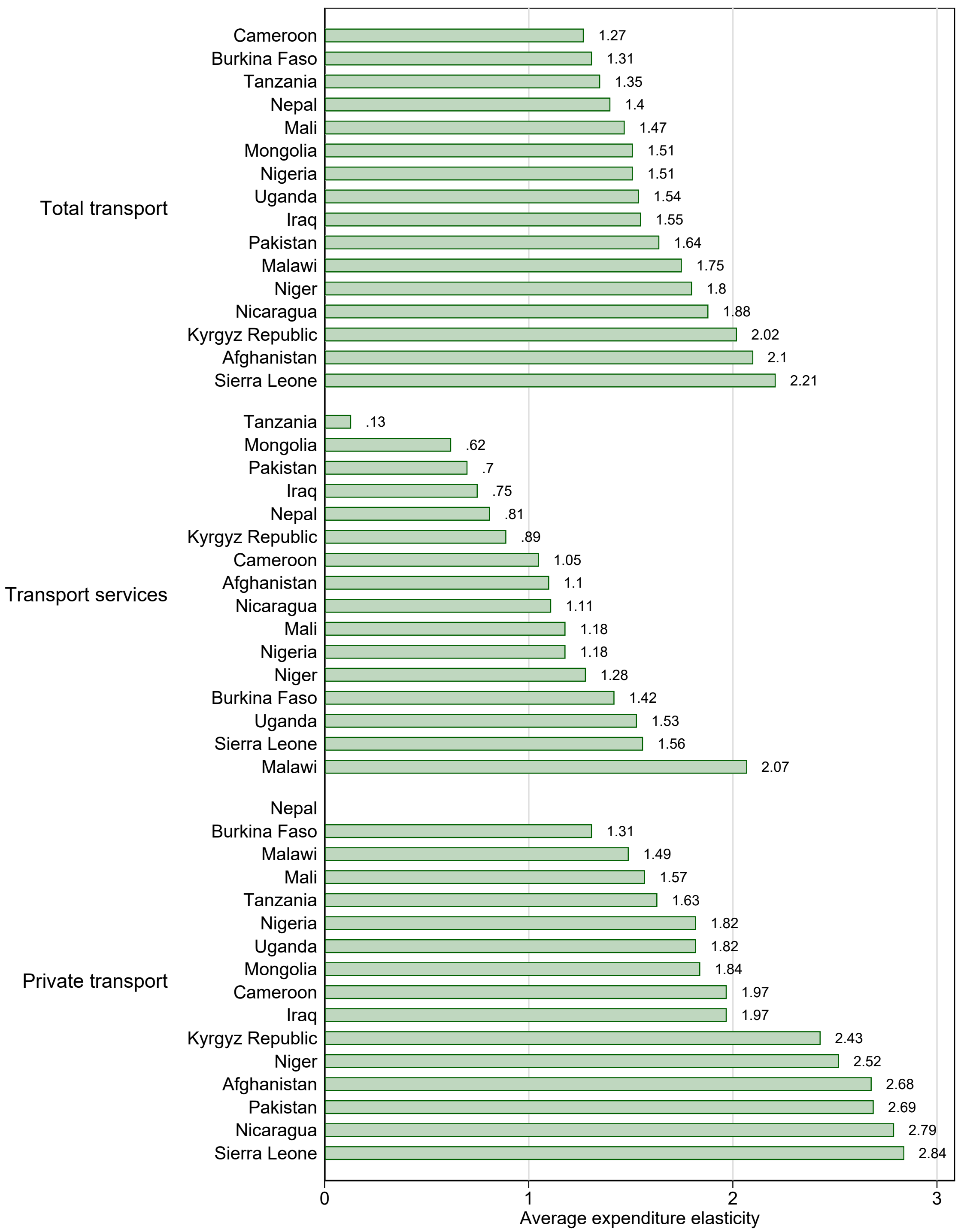
Figure 14: Average expenditure elasticity of transport



Source: Authors' calculations resulting using the ZIP model with sub-national fixed-effects as reported in Tables 4 and 5.

Elasticities per country Using a similar specification at the country level, Figure 15 reports the resulting expenditure elasticity for total transport expenditures, expenditures in transport services, and private transport expenditures. Transport elasticities vary significantly between countries for several reasons. As shown before, income levels affect the level of expenditures for all transport as well as its composition between private transport and transport services. The availability of transport services, the geography of the country, and the distribution of population and economic activities within cities and across the territory are all factors that can affect the level of transport expenditures, its composition and the expenditure elasticity. Variations in elasticities for transport services show that the consumption of transport services is clearly inferior in some countries, while being superior in some others. Elasticities for private transport are all above one, showing that private transport is a superior good in all countries. Looking at the ratio between private transport and transport services shows that as households get richer, they spend relatively more on transport services in Malawi and Burkina Faso, but relatively less on transport services in other countries. Figures B.2 and B.3 in the Appendix show that there is an association between average expenditure levels at the country level and the composition of transport expenditures. Richer countries tend to have much lower elasticity in transport services and higher elasticities in the ratio of private versus transport services. This means that households in richer countries tend to decrease their expenditures in transport services faster and increase their expenditures in private transport relatively to transport services faster too.

Figure 15: Expenditure elasticities per country



Note: The reported numbers are the elasticities of individual transport expenditures with respect to individual total expenditure. An increase of 10% of the total expenditure of an individual in a given country is associated with a $\varepsilon \times 10\%$ increase in transport expenditures.

Elasticities within country Within country, transport elasticities differ across income levels. Figure 16 reports the elasticities per decile of per capita total expenditure. The elasticity for total transport increases with the level of total expenditures and stagnates or decreases for the last 3 deciles. Richer individuals increase relatively more their transport expenditures than poorer individuals. Private transport elasticities are higher than elasticities for all transport. The transport services elasticity is around or below one across deciles, and slightly decrease as households get richer. Transport services are an inferior consumption item for the two richest deciles.

Comparing elasticities for rural and urban locations, Figure 17 shows that elasticities are higher in cities especially for private transport and for the richest households.

Figure 16: Transport elasticity per total expenditure decile

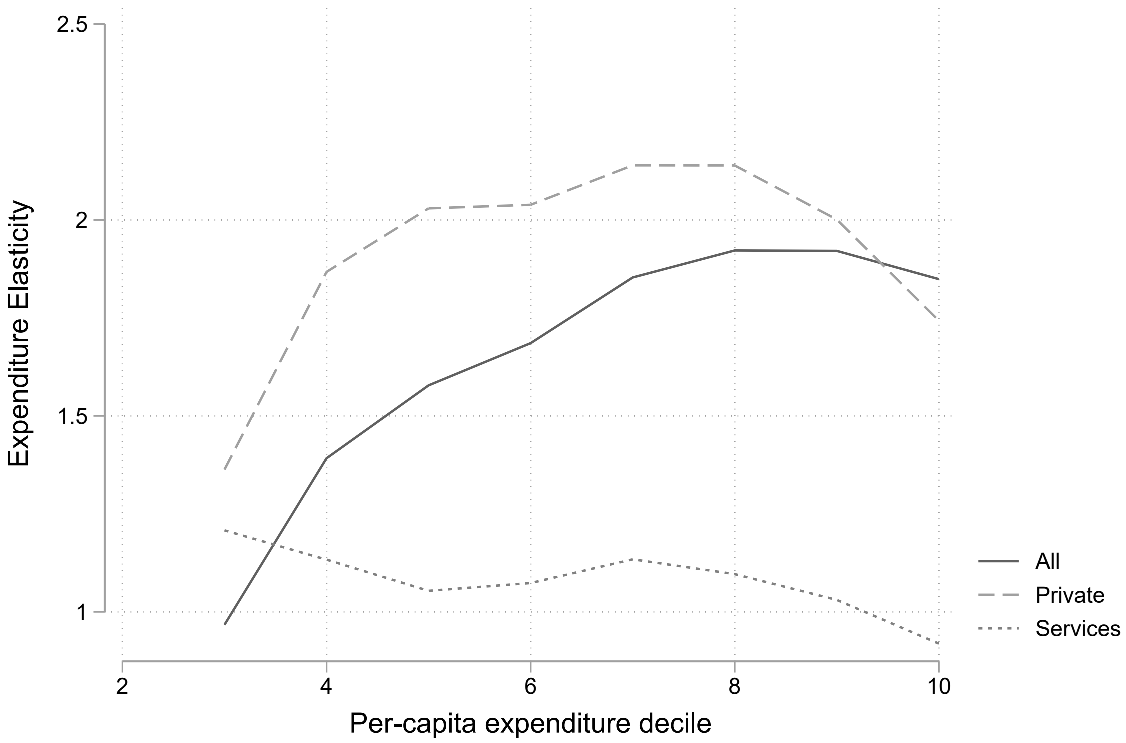
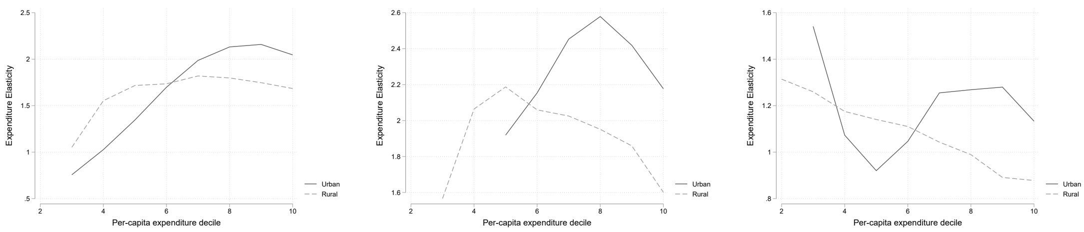


Figure 17: Elasticity per decile in urban and rural locations



(a) All (b) Private (c) Services

Note: The elasticities are estimated on the pooled sample for all countries. Non-significant coefficients are not reported.

4.5 Determinants of private transport

4.5.1 Extensive margin: the determinants of vehicle ownership

In this section, we investigate the empirical determinants of vehicle ownership at the household level. We include cars as well as other vehicles including motorcycles and bicycles. A bicycle is often the first private transport asset poorer households can afford to acquire. Motorcycles can be a cheaper and more available substitute of cars in many countries. For example, less than 5% of households own a car in Mali, Burkina Faso, Togo and Benin, but more than 30% own a motorcycle (World Bank SSAPOV harmonized survey database). While the acquisition of a bicycle does not contribute to the growth of CO2 emissions, motorcycles do but to a lesser extent than cars. This section therefore looks at the determinants of first vehicle acquisition and ensuing substitution between bicycles, motorcycles, and motor cars.

In order to quantify the determinants of vehicle ownership, we estimate the following equation:

$$Pr(ownership_i = k) = \beta_0 + \beta_1 ln\left(\frac{x_i}{n_i}\right) + \beta_2 ln(n_i) + \theta z_i + \varepsilon_i \tag{4.6}$$

The ordinal dependent variable $Pr(ownership_i = k)$ is the probability for a household to own a vehicle of type k, but not of higher order.

$$k = \begin{cases} 1 & \text{if the household does not own a vehicle} \\ 2 & \text{if the household owns a bicycle but no motor vehicle} \\ 3 & \text{if the household owns a motorcycle but no car} \\ 4 & \text{if the household owns a car.} \end{cases}$$

If a household owns more than one type of vehicle, we classify this household in the highest vehicle ownership category. For instance, k=4 if a household owns a bicycle and a car. The explanatory variables are defined as follows: x_i is total expenditure of the household i, n_i household size, and z_i a vector of other household socio-demographic characteristics, including age, gender, and educational level of household head.

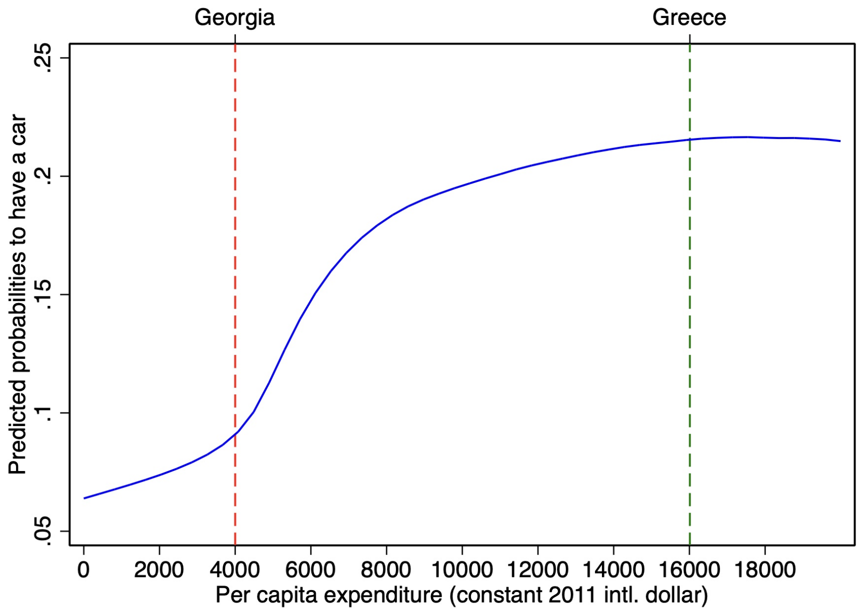
We estimate Equation 4.6 using an ordered logistic model whose results are presented in Table B.16 in the Appendix. Belonging to a wealthy, educated, and large household increases the chances of being in a higher vehicle's ownership category. As households become richer, they progress in the vehicle ownership hierarchy by switching from a low to a higher level. These results are consistent across the two specifications considered in Table B.16 in the Appendix.

Table B.17 in the Appendix provides average marginal effects that can easily be interpreted. The probability of not owning a vehicle decreases with income and education but increases with the household head's age. Doubling per-capita expenditure decreases the probability of not owning a vehicle by about ten percentage points. The probabilities of owning a vehicle (bicycle, motorcycle, and car) increase with income. However, the effect is more important for motorcycle and cars than bicycles.

To understand differences between countries, we use the ordered logistic regression to predict the average probabilities to own a vehicle in each country. Figure C.1 in the Appendix shows the different probabilities of owning a vehicle per country. For instance, a household in Niger has, on average, a 2% chance of owning a car compared to 29% in Mongolia. Burkina-Faso is an outlier as the predicted probabilities of having a bicycle or a motorcycle are much higher than in other countries. Weather and geography, cultural factors, low motorcycle prices, and the growing trade relationship between Burkina-Faso and China can partly explain the high penetration of motorcycles in this country. Figure C.1 in the Appendix shows that there are large differences in predicted probabilities of owning a car. To analyze the correlation between income and vehicle ownership, Figure C.2 in the Appendix plots the predicted probabilities of owning a vehicle against the log of GDP per capita. We find a positive correlation between the predicted probability of owning a car and GDP per capita. However there is no clear correlation pattern between the predicted probability of owning no vehicle and GDP per capita.

The transport literature has documented the relationship between vehicle ownership and income for some countries. Indeed, many studies describe an S-shape relationship between the two variables (see e.g., Lescaroux, 2010; Wu et al., 2014). We estimate a non-linear relationship between the predicted probability of having a car and per capita expenditure to verify this S-shape with our data. Figure 18 shows that our results are in line with the transport literature. Indeed, the probability of owning a car starts to increase slowly for households with expenditure below $4000 (the level of per capita expenditure in Georgia). After $4000, This probability increases sharply and stabilizes from $16000 (the level of per capita expenditure in Greece).

Figure 18: Income and car ownership - the S-shape curve



4.5.2 Intensive margin: the determinants of total distance traveled

Rising incomes not only affect vehicle availability, but also vehicle use, the number of kilometers per car in a given period, once the vehicle is acquired. For most countries, vehicle availability remains the main factor behind changes in private transport expenditures, but car use becomes an increasingly important factor in countries with growing incomes and fast urbanization. Figure 12 shows a strong correlation between country GDP per capita and distance traveled. Several factors can explain why increasing income might contribute to the rapid growth of passenger travel. The proportion of multiple vehicle households can grow. In urban locations, households might move to larger and more comfortable housing in the suburbs, thereby increasing commuting trip distances. The number and length of discretionary trips might increase. Memmott (2007) uses data from the 2001 National Household Travel Survey of U.S. Department of Transportation, Bureau of Transportation Statistics and Federal Highway Administration to look at the number of trips and average trip length per income category. He shows that, in 2001, higher income households make more trips and travel more miles than lower income households. Households in the highest income class make about 30 percent more trips, and the average length of those trips is more than 40 percent longer than trips by those in the lowest income class. Outside of the United-States, little has been done to understand the determinants of distance traveled using household or individual level data, and standard household survey data do not include consistent questions on distance traveled.

In this paper, we restrict our analysis to a cross-country panel regression using data from the International Road Federation covering a large number of countries for as many years as possible between 2000 and 2017. We regress the log of the average number of passengers car-km per household on the log of GDP per capita (Table 6). In the regression with year fixed-effects, a 1% increase in GDP per capita is associated with a 0.46% increase in km per car, which measures the intensity of car usage.

Table 6: OLS regression for total traveled distance per car

Dependent variable :	*Log Traveled distance per car*		
Log GDP per capita	0.422**	-0.173**	0.466**
	(9.62)	(-3.54)	(10.49)
Year FE	No	No	Yes
Country FE	No	Yes	No
R-squared	0.119	0.020	0.159
N. of observations	686	686	686

t statistics in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

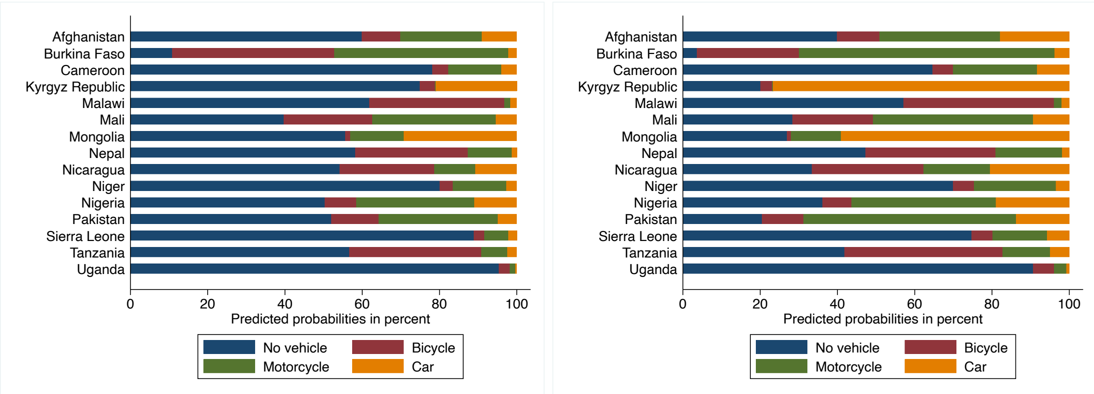
5 Rising Incomes and Transport Sector Decarbonization

The previous section has quantified the relations between income and transport expenditures, vehicle ownership, and vehicle usage. The objective of this section is to use these estimates to simulate the implications of rising incomes on transport CO2 emissions. For simplicity, we focus on private transport and assume that most of the increase in CO2 emissions will come from first-time vehicle buyers and an increase in vehicle use. We simulate the effects of rising incomes in 2035 on CO2 emissions through two channels: the increase of vehicle ownership (extensive margin) and the increase in vehicle use (intensive margin). The first subsection focuses on the extensive margin, the increase in vehicle ownership, the second on the intensive margin, the increase in vehicle use or car traveled distance.

5.1 Rising Income, Vehicle Ownership, and Carbon Emissions

The impact of rising income on vehicle ownership We use the results from Section 4.5.1 to simulate the impact of predicted income changes on vehicle ownership across countries. Using the same ordered Logit model, we predict the average probabilities to own a vehicle when incomes are at the current level (panel a of Figure 19) and at the 2035's level (panel b of Figure 19) for the countries in the LSMS sample. 2035 income levels are calculated using GDP growth predictions estimated by Fouré et al. (2012) and represent a business-as-usual scenario which does not include any change in households' behavior adapting to the new situation. As shown in Figure 19, predicted probabilities to own no vehicle decrease as incomes expand in 2035. More households own a vehicle as they get richer. More specifically, the structure of vehicle ownership will change since more households will own any type of vehicle, a motorcycle or a car, and some households will change categories, from having at most a motorcycle to acquiring a car for the first time. On average, the predicted probabilities of owning a car increase by 93% compared to a 55% increase in motorcycle ownership. These averages hide important discrepancies between countries. For instance, the increase in motorcycle ownership is larger in Burkina-Faso than in Mongolia, where car ownership is more affected by income increases. Finally, the effect of rising income on bicycle ownership is less clear as some households switch from having a bicycle only to acquiring a motorcycle or a car.

Figure 19: Income changes and vehicle ownership



(a) Income at current level

(b) Income at 2035 level

The impact of increased vehicle ownership on carbon emissions We use country-level time-series to quantify the relation between vehicle ownership and CO2 emissions. Table 7 shows the results of the regression using transport carbon emissions per capita and vehicle ownership variables from the IRF unbalanced panel of data ranging from 2000 to 2017. Column (1) shows that carbon emissions per capita from transport increase by about 35% when the average number of cars per household doubles.[9] Column (2) reports the results for motorcycle ownership. Carbon emissions per capita from transport increase by about 15% if the number of motorcycles per household doubles. This result is in line with the literature reporting lower impact of motorcycle ownership on CO2 emissions (see e.g., Vasic and Weilenmann, 2006).

[9] The coefficient might be slightly overestimated for our next step as the regression uses average vehicle number per households while our estimates report results for owning at least one vehicle. In richer countries, many households own more than one vehicle. However this concern is valid only for a few countries while our sample covers most countries in the world. Household survey data do not consistently report the total number of vehicles in the household.

Table 7: Vehicle ownership and carbon emissions

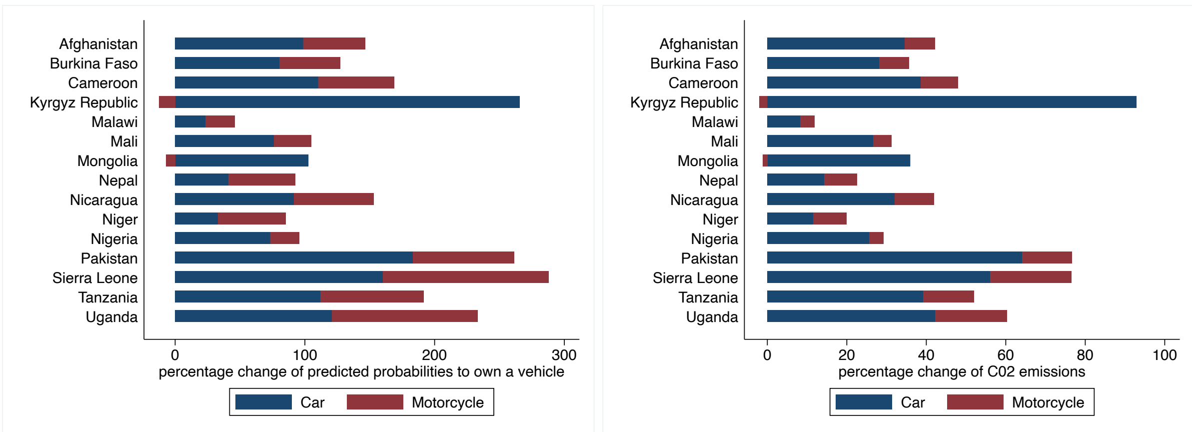
Dependent variable	(1) CO2 emissions per capita from transport (log)	(2) CO2 emissions per capita from transport (log)	(3) CO2 emissions per capita from transport (log)	(4) CO2 emissions per capita from transport (log)
Average Number of cars per household (log)	0.355***		0.391***	
	(0.034)		(0.058)	
Average Number of motorcycle per household (log)		0.156***		0.300***
		(0.013)		(0.038)
Constant	0.080**	0.182***	-0.858***	-0.860***
	(0.040)	(0.038)	(0.166)	(0.140)
Country FE	Yes	Yes	Yes	Yes
Observations	1,646	1,550	193	162
Number of countries	194 (IRF data)	194 (IRF data)	19 (LSMS survey)	19 (LSMS survey)
R-squared	0.982	0.980	0.947	0.946

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Extensive margin: rising incomes, vehicle ownership, and CO2 emissions Figure 20 uses the change in predicted probabilities from Figure 19 and the regression coefficients from Table 7 (Columns 1 and 2), to infer the impact of rising incomes on carbon emissions. Panel (b) in Figure 20 reports the increase in CO2 emissions from the increase in vehicle ownership (car and motorcycle) as income reach their predicted 2035 levels. On average, the change in car (motorcycle) ownership would lead to a 31% (9%) increase in CO2 emissions. Behind these averages, there are large differences across countries driven by the initial level of CO2 emissions and the substitution across types of vehicles.

Figure 20: Income changes and carbon emissions: the vehicle ownership channel

(a) Change in vehicle ownership (b) Final change in CO2 emissions



5.2 Rising Income, Traveled Distance, and Carbon Emissions

The impact of rising income on vehicle use Rising incomes not only affect vehicle ownership, but also vehicle use, the number of traveled kilometers per car in a given period. Richer households may drive more, in bigger cars, increasing their traveled distance and the resulting CO2 emissions. Hence, vehicle usage is a potential channel through which an increase in income may impact carbon emissions. We use the coefficient from Table 6 such that a 1% increase in GDP per capita is associated with a 0.46% increase in traveled distance per car, which measures the intensity of car use.

The impact of increased vehicle use on carbon emissions We use country-level time-series to quantify the relation between vehicle use and CO2 emissions. Table C.2 in the Appendix shows the results of the regression using transport carbon emissions per capita and traveled distance per car from the IRF unbalanced panel of data ranging from 2000 to 2017. Column (3) shows that carbon emissions per capita from transport increase by about 16% when the number of traveled kilometers per car doubles.

Intensive margin: rising incomes, vehicle use, and CO2 emissions We combine the results from the previous two channels to obtain the final increase of CO2 emissions as incomes reach their 2035 level. Vehicle use would significantly increase if income doubles, leading to a 9% increase in carbon emissions on average for the LSMS sample of countries.

5.3 Simulated Carbon Emissions from rising incomes

Until now, we have analyzed separately two channels through which rising incomes affect CO2 emissions. We now combine intensive and extensive margins to get the total effect on CO2 emissions. As described in the equation below, the total change in CO2 emissions when incomes rise is the sum of intensive margin and extensive margin plus a multiplicative combination of the two.

$$\text{Total } \Delta = \underbrace{\Delta\text{New Vehicles}}_{\text{Extensive}} + \underbrace{\Delta\text{New Usage}}_{\text{Intensive}} + \underbrace{\Delta\text{New Usage} \times \Delta\text{New Vehicles}}_{\text{Intensive margin on new cars}}$$

Figure 21 summarizes the key results of all the simulations we performed in this part. By applying the total effect on CO2 emissions formula, we find that carbon emissions from transport would increase by 52% in 2035.[10] To have a better idea of the total effect of rising incomes, Figure 22 shows the results by country in terms of the total change in CO2 emissions (percentage) and CO2 emissions' levels. There are important differences across countries. Kyrgyz Republic, Sierra Leone, Pakistan and Tanzania will experience a large percentage increase, but the absolute increase in emissions per capita will be the largest in Mongolia, Nicaragua, Nigeria and Pakistan.

[10] 31%+9%+31%*9%+9%=52%.

Figure 21: Average increase for the sample of LSMS countries for predicted 2035 income levels

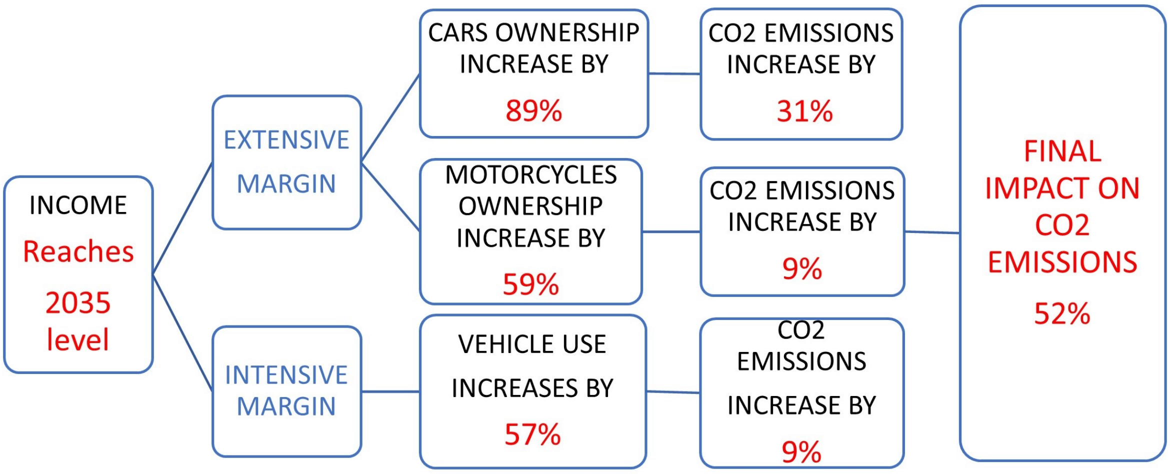
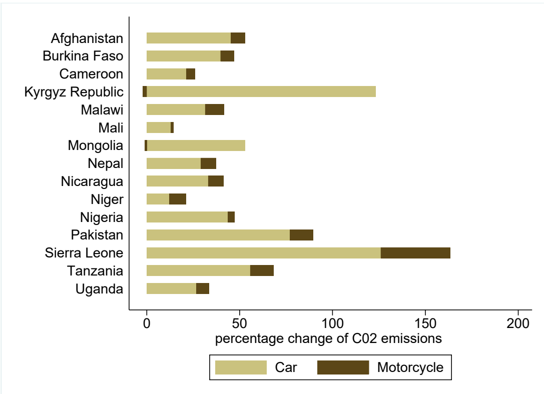
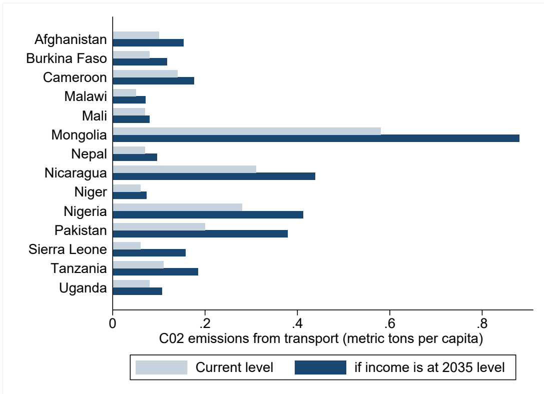


Figure 22: Total effects of Income changes in 2035 on CO2 emissions from transport

(a) Percentage change in CO2 emissions



(b) Change in CO2 emissions levels

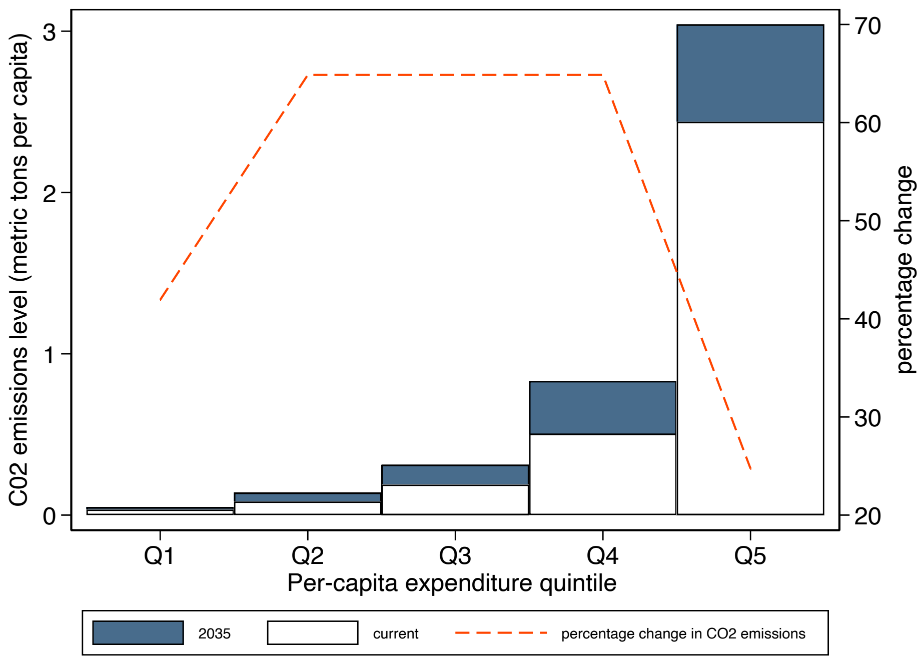


5.4 Carbon emissions across income groups

While we assume a constant increase of income for all, the effects on carbon emissions are not linear across the income distribution. Understanding how CO2 emissions contributions will change across income groups can be used in the design of environmental policies. We consider these non-linearities by investigating how per-capita expenditure quintiles contribute to carbon emissions and how these contributions will change as incomes rise in 2035. Private transport expenditure are the primary source of carbon emissions. Hence, for each per-capita expenditure quintile, we use the share of private transport expenditure per capita over the total private transport expenditure per capita to evaluate the contribution to carbon emissions.

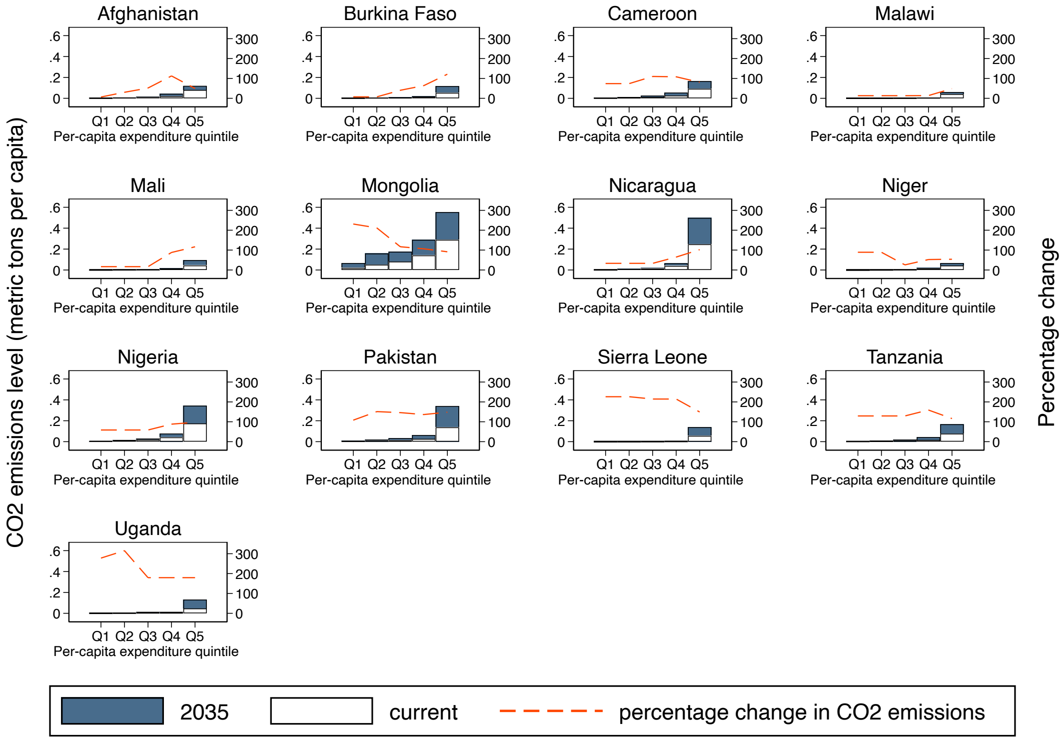
The richest quintile emits more CO2 than the rest of the income distribution. Figure 23 illustrates the contribution to carbon emissions of each per-capita expenditure quintile across countries at the current income level and in 2035. Currently, the top 20% in the expenditure distribution emits more carbon than the bottom 80%. Differences between the bottom and top quintiles are enormous. The richest quintile emits 75% of total carbon emissions while the poorest quintile emits only 1%. As income rise in 2035, the level of carbon emissions per expenditure quintile increases for all groups but at different pace. Income groups in the middle catch up as the pace of increase is higher. The increase for the bottom 80% is about twice that of the top 20%. Carbon emissions from the richest quintile increase by 25% compared to a 65% change for the middle quintiles (second, third and fourth quintiles) and a 42% change for the poorest quintile. Nevertheless, the richest quintile will remain the main contributor to carbon emissions in 2035. Overall, our results suggest while the share of emissions from the top 20% will decrease as incomes rise in 2035, the top 20% remain by far the main group contributing to CO2 emissions.

Figure 23: Current and simulated CO2 emissions per expenditure quintiles



While CO2-emission distributions vary across countries, emissions remain highly concentrated in the top quintile of the total expenditure distribution. Figure 24 shows the level of carbon emissions by expenditure quintile within countries at the current income level and 2035. The richest quintile contributes much more to carbon emissions than poorer quintiles for all countries. Concentration in carbon emissions is less important in countries such as Mongolia and Nigeria. As incomes rise in 2035, the percentage change in carbon emissions per quintile decreases for most countries. For these countries, the concentration of carbon emissions will decrease. However, the gap in terms of carbon emissions between the richest and poorest quintiles will widen for some countries such as Burkina Faso, Mali, and Nicaragua.

Figure 24: Current and simulated CO2 emissions per expenditure quintile per country



6 Conclusion

This paper aims to understand how economic development impacts transport demand and the consequences for carbon emissions from the transport sector. Using household surveys data, we estimate the determinants of transport demand. We find that transport expenditures and vehicle ownership will increase significantly as households and countries get richer. As countries get richer, households will increase their relative spending on transport, be more likely to own a car, and switch from public to private transport mode. In poorer countries, a large share of households, currently not spending on transport, will start using transport services or want to own a vehicle. The demand for private vehicles is therefore expected to increase significantly as countries get richer. These results suggest a future steep growth of emissions as incomes expand. According to our simulations, higher predicted 2035 incomes will increase vehicle ownership and usage, leading to an average increase of 52% in transport CO2 emissions for our sample of 18 countries. Finally we show that the distribution of emissions across income groups is highly concentrated among the richest households. This concentration is expected to slightly decrease for the whole sample of countries, increase in some countries, but decrease in others.

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Appendix material

This set of appendices is structured as follows. Appendix A provides additional tables on the data we use. Appendix B provides additional results for Section 4. Appendix C provides additional results for the simulations.

A Data

Table A.1: Share of households with zero-transport expenditures per country

Country	Survey year	% of all-zero observation
Burkina Faso	2014	24%
Ethiopia	2015/16	N.A
Iraq	2012	34%
Malawi	2016/17	65%
Mali	2014/15	41%
Nepal	2010/11	15%
Niger	2014/15	55%
Nigeria	2015/16	30%
Tanzania	2014/15	15%
Uganda	2015/16	46%
Afghanistan	2016/17	28%
Cameroon	2014	7%
Kyrgyz Republic	2013	2%
Mongolia	2016	16%
Nicaragua	2014	27%
Pakistan	2013/14	4%
Sierra Leone	2018	82%
South Africa	2014/15	0%

Table A.2: Dealing with durables transport using real interest and depreciation rates

Country	Real interest rate	Depreciation rate (median)	Survey year
Afghanistan	12.14 %	N/A	2017
Burkina Faso	5.99 %	19.1 %	2014
Cameroon	13.91 %	N/A	2014
Ethiopia	-17.1 %	N/A	2016
Iraq	10.84 %	N/A	2012
Kyrgyz Republic	10.81 %	N/A	2014
Malawi	22.15 %	5.74 %	2017
Mali	2.21 %	18.3 %	2015
Mongolia	17.13 %	N/A	2016
Nepal	-6.21 %	N/A	2011
Nicaragua	4.75 %	N/A	2014
Niger	5.77 %	15.6 %	2014
Nigeria	6.87 %	N/A	2016
Pakistan	4.02 %	8.16 %	2014
Sierra Leone	8.65 %	N/A	2018
South Africa	4.04 %	N/A	2015
Tanzania	9.67 %	7.18 %	2015
Uganda	18.23 %	N/A	2016

B Transport elasticities

B.1 Regression tables with square variables

Table B.7: All transport: PPML and ZIP results for specification (2) with square variable

	(1) OLS	(2) PPML	(3) ZIP	(4) OLS	(5) PPML	(6) ZIP
main						
Log per cap. exp.	1.351**	3.720**	3.129**	1.351**	3.616**	3.054**
	(33.15)	(41.42)	(36.35)	(33.15)	(38.71)	(34.28)
Log per cap. exp. × Log per cap. exp.	-0.0129**	-0.146**	-0.118**	-0.0129**	-0.139**	-0.112**
	(-4.70)	(-26.59)	(-22.37)	(-4.70)	(-24.35)	(-20.64)
Age of head	-0.00233**	-0.00239**	-0.000916*	-0.00233**	-0.00242**	-0.000879*
	(-9.43)	(-6.42)	(-2.55)	(-9.43)	(-6.62)	(-2.50)
Complete secondary education	0.147**	0.111**	0.0986**	0.147**	0.114**	0.0925**
	(16.77)	(9.37)	(8.92)	(16.77)	(9.61)	(8.39)
Log household size	0.0856**	0.211**	0.0702**	0.0856**	0.226**	0.0761**
	(12.18)	(20.26)	(6.94)	(12.18)	(21.46)	(7.46)
Urban	-0.167**	-0.158**	-0.145**	-0.167**	-0.140**	-0.117**
	(-21.52)	(-14.97)	(-14.47)	(-21.52)	(-12.41)	(-10.91)
Female	-0.269**	-0.420**	-0.362**	-0.269**	-0.419**	-0.359**
	(-26.68)	(-24.30)	(-22.04)	(-26.68)	(-24.45)	(-22.13)
inflate						
Log per cap. exp.			-0.530**			-0.669**
			(-5.52)			(-6.32)
Log per cap. exp. × Log per cap. exp.			-0.0440**			-0.0371**
			(-6.56)			(-5.01)
Age of head			0.00570**			0.00696**
			(11.15)			(12.77)
Complete secondary education			-0.0687**			-0.152**
			(-3.38)			(-6.65)
Log household size			-1.248**			-1.342**
			(-79.89)			(-79.17)
Urban			0.0781**			0.207**
			(4.43)			(9.86)
Female			0.441**			0.535**
			(21.80)			(24.87)
Country FE	Yes	Yes	Yes	No	No	No
Subnational FE	No	No	No	Yes	Yes	Yes
R-squared	0.553			0.553		
N. of observations	119060	153133	153133	119060	153133	153133

t statistics in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Note: The first part of the table reports the second stage of the ZIP model, the main regression, while the second part of the table reports the first stage of the ZIP model, the 'inflate' part.

Table B.1: PPML and ZIP results for specification (2) with square variable

	(1) OLS	(2) PPML	(3) ZIP	(4) OLS	(5) PPML	(6) ZIP
main						
Log per cap. exp.	1.351**	3.720**	3.129**	1.351**	3.616**	3.054**
	(33.15)	(41.42)	(36.35)	(33.15)	(38.71)	(34.28)
Log per cap. exp. × Log per cap. exp.	-0.0129**	-0.146**	-0.118**	-0.0129**	-0.139**	-0.112**
	(-4.70)	(-26.59)	(-22.37)	(-4.70)	(-24.35)	(-20.64)
Age of head	-0.00233**	-0.00239**	-0.000916*	-0.00233**	-0.00242**	-0.000879*
	(-9.43)	(-6.42)	(-2.55)	(-9.43)	(-6.62)	(-2.50)
Complete secondary education	0.147**	0.111**	0.0986**	0.147**	0.114**	0.0925**
	(16.77)	(9.37)	(8.92)	(16.77)	(9.61)	(8.39)
Log household size	0.0856**	0.211**	0.0702**	0.0856**	0.226**	0.0761**
	(12.18)	(20.26)	(6.94)	(12.18)	(21.46)	(7.46)
Urban	-0.167**	-0.158**	-0.145**	-0.167**	-0.140**	-0.117**
	(-21.52)	(-14.97)	(-14.47)	(-21.52)	(-12.41)	(-10.91)
Female	-0.269**	-0.420**	-0.362**	-0.269**	-0.419**	-0.359**
	(-26.68)	(-24.30)	(-22.04)	(-26.68)	(-24.45)	(-22.13)
inflate						
Log per cap. exp.			-0.530**			-0.669**
			(-5.52)			(-6.32)
Log per cap. exp. × Log per cap. exp.			-0.0440**			-0.0371**
			(-6.56)			(-5.01)
Age of head			0.00570**			0.00696**
			(11.15)			(12.77)
Complete secondary education			-0.0687**			-0.152**
			(-3.38)			(-6.65)
Log household size			-1.248**			-1.342**
			(-79.89)			(-79.17)
Urban			0.0781**			0.207**
			(4.43)			(9.86)
Female			0.441**			0.535**
			(21.80)			(24.87)
Country FE	Yes	Yes	Yes	No	No	No
Subnational FE	No	No	No	Yes	Yes	Yes
R-squared	0.553			0.553		
N. of observations	119060	153133	153133	119060	153133	153133

t statistics in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Note: The first part of the table reports the second stage of the ZIP model, the main regression, while the second part of the table reports the first stage of the ZIP model, the ‘inflate’ part.

Table B.2: Average expenditure elasticity

	(1) PPML	(2) ZIP	(3) PPML	(4) ZIP
Log per cap. exp.	1.200**	1.358**	1.209**	1.378**
Country FE	Yes	Yes	No	No
Subnational FE	No	No	Yes	Yes

Table B.3: Public transport: PPML and ZIP results for specification (2) with square variable

	(1) OLS	(2) PPML	(3) ZIP	(4) OLS	(5) PPML	(6) ZIP
main						
Log per cap. exp.	0.544**	0.782**	0.625**	61.47**	0.788**	0.646**
	(93.40)	(81.75)	(62.90)	(37.67)	(74.77)	(62.30)
Age of head	-0.000371	-0.00253**	-0.000576	-0.125**	-0.00285**	-0.000117
	(-1.59)	(-6.17)	(-1.59)	(-3.39)	(-7.11)	(-0.34)
Complete secondary education	0.146**	0.106**	0.140**	23.13**	0.0489**	0.0832**
	(17.97)	(6.95)	(10.51)	(12.47)	(3.26)	(6.39)
Log household size	-0.444**	-0.248**	-0.390**	-30.96**	-0.265**	-0.410**
	(-65.31)	(-22.03)	(-37.41)	(-23.38)	(-22.99)	(-38.87)
Urban	0.0201**	0.129**	0.0143	6.320**	-0.00984	-0.0368**
	(2.75)	(9.47)	(1.24)	(5.33)	(-0.68)	(-2.90)
Female	0.0291**	0.0902**	0.0182	4.656**	0.0744**	0.0126
	(3.27)	(5.50)	(1.25)	(2.83)	(4.61)	(0.89)
inflate						
Log per cap. exp.			-0.610**			-0.566**
			(-65.30)			(-53.02)
Age of head			0.00322**			0.00495**
			(7.57)			(10.83)
Complete secondary education			0.0941**			0.0793**
			(5.82)			(4.44)
Log household size			-0.515**			-0.539**
			(-41.63)			(-40.04)
Urban			-0.241**			-0.00783
			(-16.98)			(-0.48)
Female			-0.188**			-0.165**
			(-10.81)			(-8.94)
Country FE	Yes	Yes	Yes	No	No	No
Subnational FE	No	No	No	Yes	Yes	Yes
R-squared	0.534			0.116		
N. of observations	85185	153133	153133	153255	153133	153133

t statistics in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Note: The first part of the table reports the second stage of the ZIP model, the main regression, while the second part of the table reports the first stage of the ZIP model, the 'inflate' part.

Table B.4: Average expenditure elasticity for public transport

	(1) PPML	(2) ZIP	(3) ZIP
Log per cap. exp.	0.782**	0.895**	0.897**
Country FE	Yes	Yes	No
Subnational FE	No	No	Yes

Table B.5: Private transport: PPML and ZIP results for specification (2) with square variable

	(1) OLS	(2) PPML	(3) ZIP	(4) OLS	(5) PPML	(6) ZIP
main						
Log per cap. exp.	1.227**	1.352**	1.061**	1.261**	1.361**	1.049**
	(134.47)	(120.71)	(99.69)	(135.33)	(115.12)	(90.82)
Age of head	-0.00313**	-0.00242**	-0.000320	-0.00258**	-0.00241**	-0.000412
	(-7.68)	(-4.49)	(-0.71)	(-6.49)	(-4.58)	(-0.93)
Complete secondary education	0.221**	0.146**	0.0836**	0.213**	0.165**	0.0620**
	(15.28)	(8.29)	(6.09)	(14.59)	(9.47)	(4.52)
Log household size	0.0682**	0.368**	-0.108**	0.108**	0.396**	-0.110**
	(5.76)	(23.38)	(-8.35)	(9.07)	(25.23)	(-8.39)
Urban	-0.179**	-0.209**	-0.0668**	-0.154**	-0.143**	-0.0568**
	(-14.08)	(-13.77)	(-5.48)	(-11.90)	(-9.02)	(-4.43)
Female	-0.432**	-0.756**	-0.245**	-0.432**	-0.743**	-0.244**
	(-22.22)	(-24.42)	(-10.25)	(-22.65)	(-24.32)	(-10.48)
inflate						
Log per cap. exp.			-0.937**			-1.153**
			(-94.28)			(-94.24)
Age of head			0.00291**			0.00274**
			(6.80)			(5.86)
Complete secondary education			-0.0568**			-0.162**
			(-3.72)			(-9.45)
Log household size			-1.287**			-1.508**
			(-96.03)			(-98.50)
Urban			0.383**			0.311**
			(27.59)			(18.91)
Female			0.978**			1.096**
			(51.83)			(52.41)
Country FE	Yes	Yes	Yes	No	No	No
Subnational FE	No	No	No	Yes	Yes	Yes
R-squared	0.538			0.568		
N. of observations	72979	153133	153133	72889	152365	147153

t statistics in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Note: The first part of the table reports the second stage of the ZIP model, the main regression, while the second part of the table reports the first stage of the ZIP model, the 'inflate' part.

Table B.6: Average expenditure elasticity for private transport

	(1) PPML	(2) ZIP	(3) PPML	(4) ZIP
Log per cap. exp.	1.352**	1.552**	1.361**	1.649**
Country FE	Yes	Yes	No	No
Subnational FE	No	No	Yes	Yes

Table B.8: Transport services: PPML and ZIP results for specification (2) with square variable

	(1) OLS	(2) PPML	(3) ZIP	(4) OLS	(5) PPML	(6) ZIP
main						
Log per cap. exp.	1.536**	3.056**	1.643**	1.536**	2.850**	1.481**
	(34.05)	(26.73)	(15.82)	(34.05)	(23.92)	(14.16)
Log per cap. exp. × Log per cap. exp.	-0.0654**	-0.137**	-0.0610**	-0.0654**	-0.124**	-0.0500**
	(-21.85)	(-18.82)	(-9.21)	(-21.85)	(-16.41)	(-7.52)
Age of head	-0.0000920	-0.00204**	-0.000461	-0.0000920	-0.00234**	0.00000777
	(-0.40)	(-5.01)	(-1.28)	(-0.40)	(-5.88)	(0.02)
Complete secondary education	0.159**	0.105**	0.137**	0.159**	0.0508**	0.0820**
	(19.60)	(7.03)	(10.35)	(19.60)	(3.44)	(6.32)
Log household size	-0.452**	-0.237**	-0.382**	-0.452**	-0.257**	-0.404**
	(-66.55)	(-21.26)	(-36.81)	(-66.55)	(-22.38)	(-38.52)
Urban	0.00894	0.0934**	-0.000608	0.00894	-0.0366*	-0.0481**
	(1.23)	(7.01)	(-0.05)	(1.23)	(-2.52)	(-3.79)
Female	0.0286**	0.0991**	0.0225	0.0286**	0.0822**	0.0157
	(3.22)	(6.06)	(1.55)	(3.22)	(5.10)	(1.11)
inflate						
Log per cap. exp.			-2.693**			-2.698**
			(-39.61)			(-34.59)
Log per cap. exp. × Log per cap. exp.			0.140**			0.143**
			(31.26)			(27.83)
Age of head			0.00231**			0.00397**
			(5.41)			(8.65)
Complete secondary education			0.0463**			0.0296
			(2.84)			(1.64)
Log household size			-0.494**			-0.518**
			(-39.80)			(-38.28)
Urban			-0.220**			0.0157
			(-15.48)			(0.95)
Female			-0.187**			-0.165**
			(-10.74)			(-8.89)
Country FE	Yes	Yes	Yes	No	No	No
Subnational FE	No	No	No	Yes	Yes	Yes
R-squared	0.538			0.538		
N. of observations	85185	153133	153133	85185	153133	153133

t statistics in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Note: The first part of the table reports the second stage of the ZIP model, the main regression, while the second part of the table reports the first stage of the ZIP model, the 'inflate' part.

Table B.9: Private transport: PPML and ZIP results for specification (2) with square variable

	(1) OLS	(2) PPML	(3) ZIP	(4) OLS	(5) PPML	(6) ZIP
main						
Log per cap. exp.	0.848**	4.914**	3.544**	0.848**	4.931**	3.526**
	(16.12)	(38.65)	(35.06)	(16.12)	(37.68)	(32.90)
Log per cap. exp. × Log per cap. exp.	0.0269**	-0.202**	-0.142**	0.0269**	-0.202**	-0.141**
	(7.51)	(-26.71)	(-23.37)	(7.51)	(-25.92)	(-21.92)
Age of head	-0.00346**	-0.00225**	0.0000166	-0.00346**	-0.00209**	0.000106
	(-8.48)	(-4.31)	(0.04)	(-8.48)	(-4.09)	(0.25)
Complete secondary education	0.204**	0.108**	0.0677**	0.204**	0.133**	0.0502**
	(14.07)	(6.50)	(5.24)	(14.07)	(8.05)	(3.86)
Log household size	0.0828**	0.392**	-0.0962**	0.0828**	0.421**	-0.0980**
	(7.04)	(25.60)	(-7.57)	(7.04)	(27.31)	(-7.56)
Urban	-0.185**	-0.250**	-0.0840**	-0.185**	-0.181**	-0.0801**
	(-14.67)	(-17.55)	(-7.26)	(-14.67)	(-11.99)	(-6.51)
Female	-0.430**	-0.749**	-0.243**	-0.430**	-0.738**	-0.243**
	(-22.21)	(-24.21)	(-10.25)	(-22.21)	(-24.12)	(-10.47)
inflate						
Log per cap. exp.			0.0798			-0.208*
			(1.10)			(-2.35)
Log per cap. exp. × Log per cap. exp.			-0.0671**			-0.0617**
			(-13.82)			(-10.54)
Age of head			0.00333**			0.00314**
			(7.73)			(6.63)
Complete secondary education			-0.0422**			-0.152**
			(-2.74)			(-8.81)
Log household size			-1.299**			-1.518**
			(-95.67)			(-97.82)
Urban			0.373**			0.301**
			(26.77)			(18.20)
Female			0.977**			1.095**
			(51.37)			(51.98)
Country FE	Yes	Yes	Yes	No	No	No
Subnational FE	No	No	No	Yes	Yes	Yes
R-squared	0.540			0.540		
N. of observations	72896	147153	153133	72896	147153	147153

t statistics in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Note: The first part of the table reports the second stage of the ZIP model, the main regression, while the second part of the table reports the first stage of the ZIP model, the 'inflate' part.

B.2 Elasticities with the ZIP model, subnational FEs and square expenditures.

Table B.10: Average expenditure elasticity

	(1) ZIP	(2) PPML	(3) ZIP
Log per cap. exp.	1.656**	1.578**	1.666**
Country FE	Yes	No	No
Subnational FE	No	Yes	Yes

Table B.11: Average expenditure elasticity for public transport

	(1) PPML	(2) ZIP	(3) PPML	(4) ZIP
Log per cap. exp.	1.046**	1.066**	1.028**	1.047**
Country FE	Yes	Yes	No	No
Subnational FE	No	No	Yes	Yes

Table B.12: Average expenditure elasticity for private transport

	(1) ZIP	(2) PPML	(3) ZIP
Log per cap. exp.	1.928**	1.947**	2.021**
Country FE	Yes	No	No
Subnational FE	No	Yes	Yes

Table B.13: Average expenditure elasticity for total transport per quintile

	(1) ZIP	(2) ZIP	(3) ZIP	(4) ZIP	(5) ZIP
Log per cap. exp.	2.077**	1.754**	1.592**	1.592**	1.197**
Country FE	No	No	No	No	No
Subnational FE	Yes	Yes	Yes	Yes	Yes

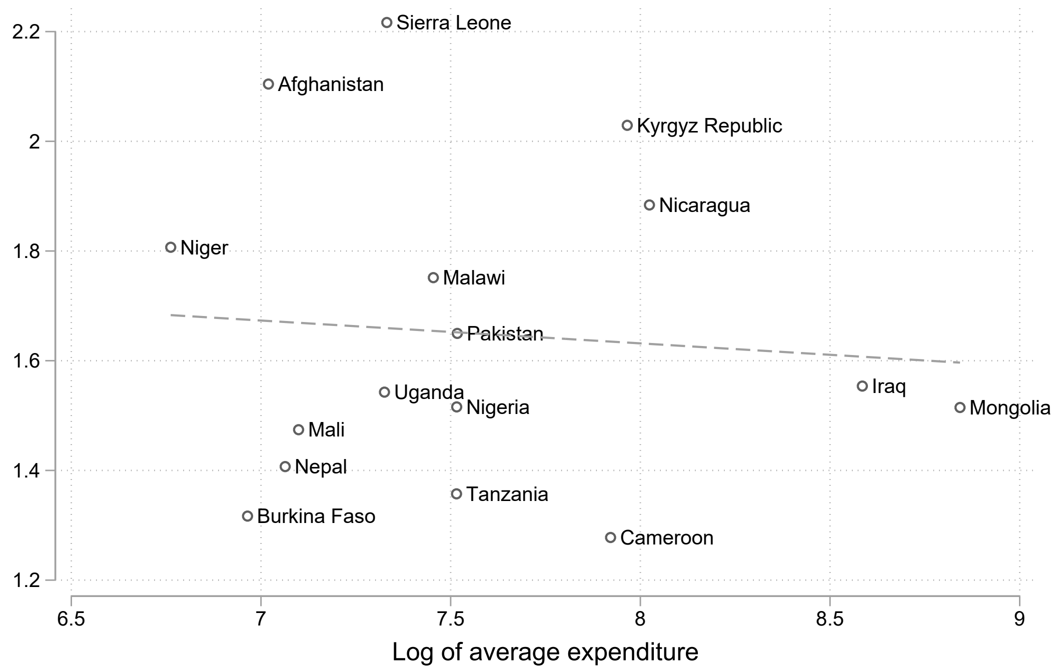
Table B.14: Average expenditure elasticity for total transport per quintile

	(1) ZIP	(2) ZIP	(3) ZIP	(4) ZIP	(5) ZIP
Log per cap. exp.	0.814**	1.288**	1.009**	0.831**	0.607**
Country FE	No	No	No	No	No
Subnational FE	Yes	Yes	Yes	Yes	Yes

Table B.15: Average expenditure elasticity for total transport per quintile

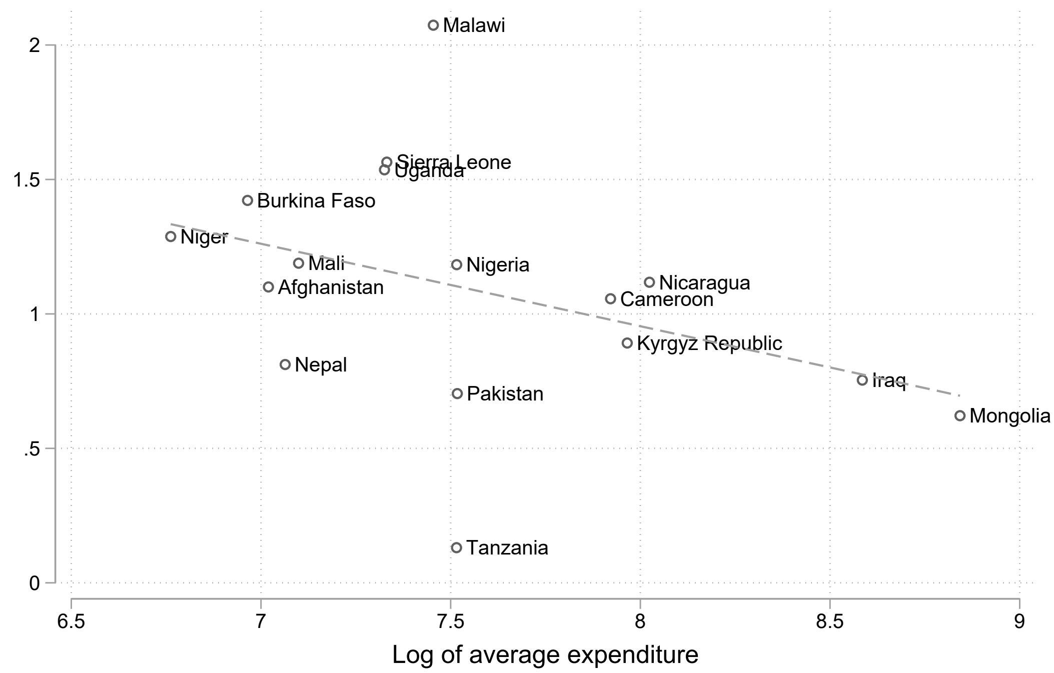
	(1) ZIP	(2) ZIP	(3) ZIP	(4) ZIP	(5) ZIP
Log per cap. exp.	1.657**	2.077**	2.077**	2.100**	1.414**
Country FE	No	No	No	No	No
Subnational FE	Yes	Yes	Yes	Yes	Yes

Figure B.1: Expenditure elasticities for all and average expenditure levels at the country level



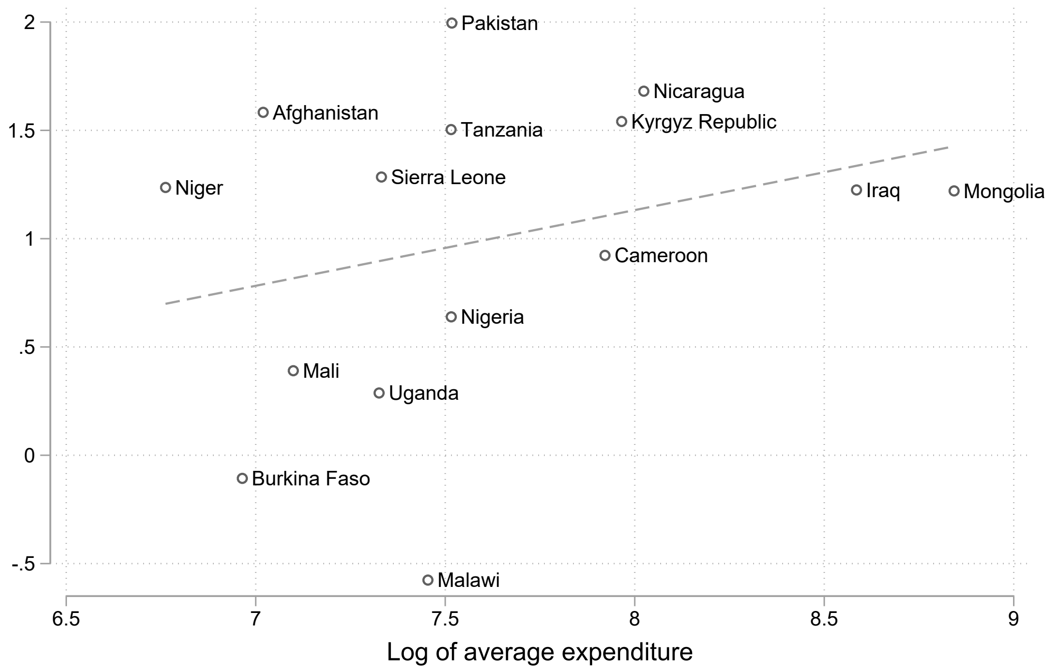
Source: Authors' calculations

Figure B.2: Expenditure elasticities for transport services and average expenditure levels at the country level



Source: Authors' calculations

Figure B.3: Expenditure elasticities for the ratio of private transport versus services and average expenditure levels at the country level



Source: Authors' calculations

Table B.16: Ownership regressions : ordered Logit model

	(1) $Pr(ownership_i = k)$	(2) $Pr(ownership_i = k)$
Log of Per capita expenditure	0.970***	1.113***
	(99.05)	(102.98)
Age of the HH head	-0.00564***	-0.00579***
	(-13.72)	(-13.67)
Urban	-0.302***	-0.228***
	(-21.94)	(-15.08)
Education of HH head (secondary complete)	0.235***	0.325***
	(14.72)	(19.52)
Log of HH size	1.319***	1.445***
	(105.15)	(108.44)
Country FE	Yes	No
Subnational FE	No	Yes
R-squared		
N. of observations	138118	138118

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

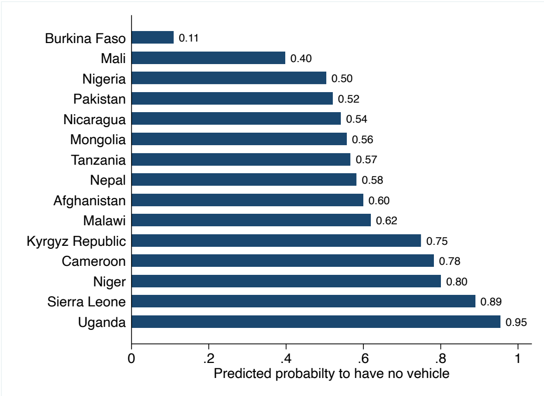
Table B.17: Ownership regressions with Country FE : Average Marginal Effects

VARIABLES	(1) Log of Per capita expenditure	(2) Age of the HH head	(3) Urban	(4) Education of HH head (secondary complete)	(5) Log of HH size
Pr (HH does not own a Vehicle)	-0.173***	0.001***	0.054***	-0.042***	-0.236***
	(0.002)	(0.000)	(0.002)	(0.003)	(0.002)
Pr (HH owns a Bicycle)	0.027***	-0.000***	-0.008***	0.007***	0.037***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pr (HH owns a Motorcycle)	0.077***	-0.000***	-0.024***	0.019***	0.105***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Pr (HH owns a Car)	0.069***	-0.000***	-0.021***	0.017***	0.094***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Observations	138,118	138,118	138,118	138,118	138,118
Country FE	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	No	No	No

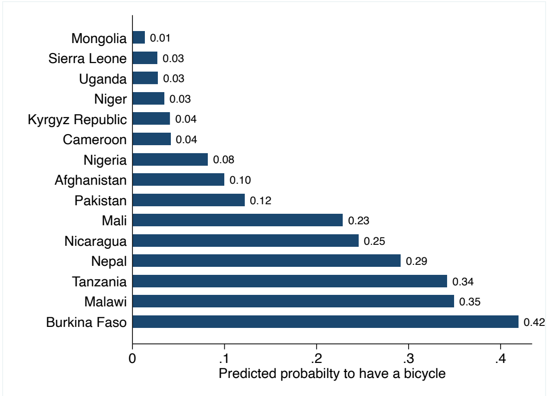
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

C Simulations

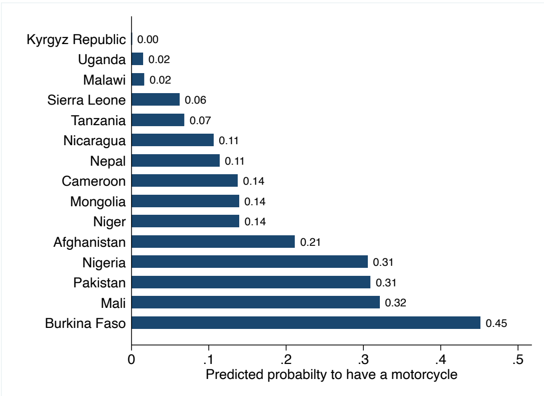
Figure C.1: Predicted probabilities to own a vehicle



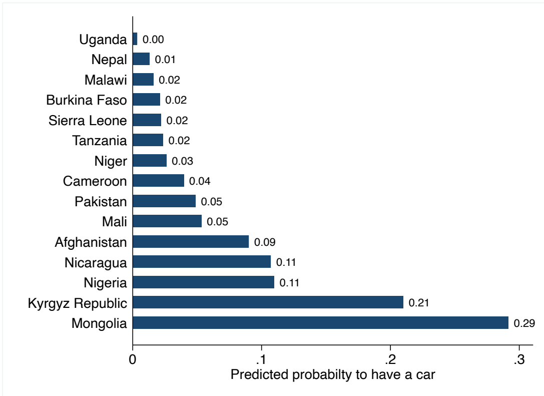
(a) Pr (HH does not own a Vehicle)



(b) Pr (HH owns a bicycle)

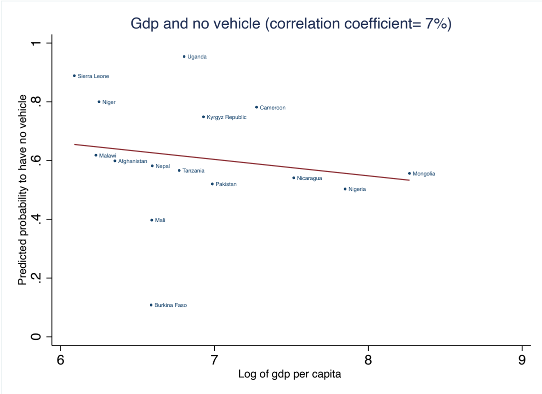


(c) Pr (HH owns a Motorcycle)

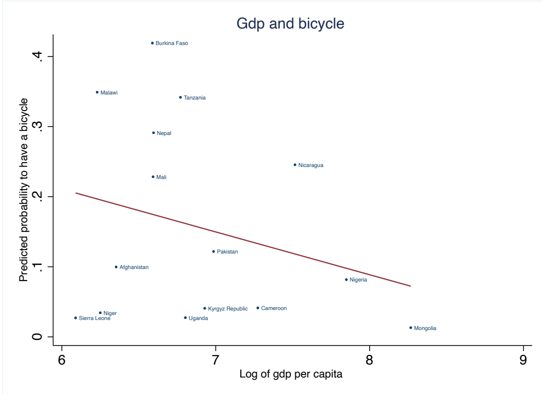


(d) Pr (HH owns a Car)

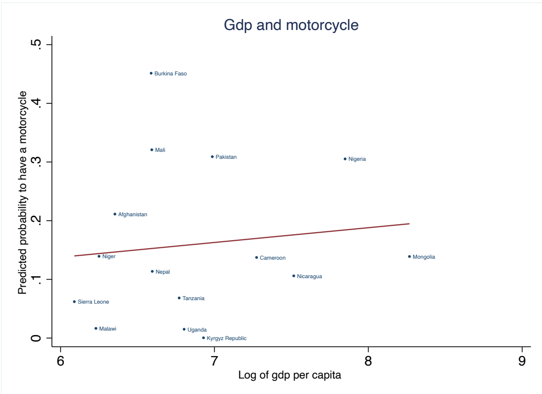
Figure C.2: Predicted probabilities to own a vehicle and GDP



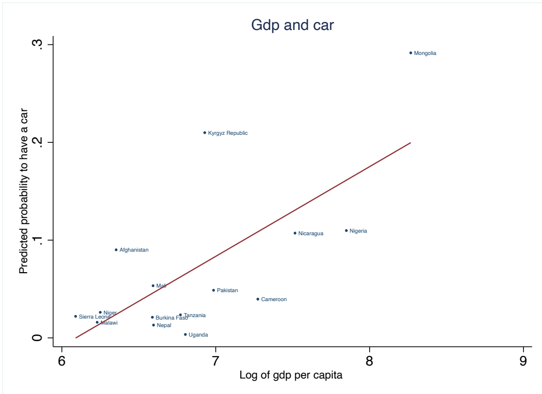
(a) Pr (HH does not own a Vehicle)



(b) Pr (HH owns a bicycle)



(c) Pr (HH owns a Motorcycle)



(d) Pr (HH owns a Car)

Table C.1: Inputs for simulation

Country	**Survey year**	**Year when income doubles**	**Ratio of income in 2035 over current income***	**Ratio of income in 2040 over current income***
Afghanistan	2017	2031	2.13	2.57
Albania	2012	2027	2.77	3.42
Burkina Faso	2014	2030	2.44	3.04
Cameroon	2014	2038	1.91	2.26
Kyrgyz Republic	2014	2026	3.09	3.96
Malawi	2017	2039	1.87	2.27
Mali	2015	2037	2.01	2.43
Mongolia	2016	2027	2.84	3.61
Nepal	2011	2027	2.74	3.39
Nicaragua	2014	2034	2.20	2.71
Niger	2014	2037	1.93	2.29
Nigeria	2016	2035	2.03	2.46
Pakistan	2014	2035	2.10	2.54
Sierra Leone	2018	2027	2.57	3.19
South Africa	2015	2038	1.75	2.00
Tanzania	2015	2029	2.65	3.40
Uganda	2016	2034	2.19	2.73
Average ratio			**2.28**	**2.80**

Notes: Our calculations are based on GDP per capita growth predictions provided by CEPII. Current income means the income at the survey year.

Table C.2: Vehicle use and carbon emissions: OLS results

	Log CO2 emissions		
Log annual kilometer per car	0.158**	-0.0430**	0.158**
	(7.97)	(-4.33)	(7.85)
Year FE	No	No	Yes
Country FE	No	Yes	No
R-squared	0.083	0.029	0.105
N. of observations	702	702	702

t statistics in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$