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Javier Morales Sarriera, Lourdes Rodriguez Chamussy, Jorge Puig y Evelyn Vezza

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Universal and targeted subsidies in urban bus transport: distributional effects and policy lessons from Argentina^{*}

Javier Morales Sarriera

Lourdes Rodriguez Chamussy

Jorge Puig

Evelyn Vezza

Abstract

This paper examines the distributional effects of bus transport subsidies in Argentina, a country with a longstanding system of fare support. A key feature of this subsidy scheme is the coexistence of a universal flat subsidy for all users and targeted mechanisms aimed at protecting lower-income groups, alongside integrated fare discounts for multi-stage trips. Using household survey data, mobility microdata, and administrative records, we estimate the distributional incidence of these subsidies. We find that while subsidies are progressive in relative terms, they exhibit weak targeting in absolute terms, with a substantial share of benefits accruing to middle- and high-income users. This pattern is largely driven by the dominance of the universal subsidy over more targeted instruments. The paper highlights the equity challenges inherent in mixed subsidy structures and offers policy lessons for countries seeking to redesign fare systems, improve targeting, or rationalize public transport subsidies under fiscal constraints.

JEL CODES: H22, D31, D78, Q48.

KEYWORDS: distributional incidence, subsidies, urban public transport, Argentina.

^{*}Javier Morales Sarriera, Lourdes Rodriguez Chamussy, and Evelyn Vezza are affiliated with the World Bank. Jorge Puig is affiliated with the Center for Distributive, Labor, and Social Studies (CEDLAS) and the Center for Public Finance Studies (CEFIP), IIE-FCE, National University of La Plata (UNLP). Email for contact: jorge.puig@econo.unlp.edu.ar. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, the Executive Directors of the World Bank, or the governments they represent.

1 Introduction

Public transport subsidies are widely used around the world and often represent a significant component of urban transport policy (Guzman & Hessel, 2022). Despite their widespread use and fiscal relevance, relatively little empirical evidence exists on how public transport subsidies are actually distributed across income groups in real-world settings, and how different design features (such as universal versus targeted fare reductions) shape their distributional effects (Asensio *et al.*, 2003; Bueno Cadena *et al.*, 2016; Börjesson *et al.*, 2020). In this paper, we contribute to the empirical evidence by examining the design and distributional effects of subsidies for urban bus transport in the Metropolitan Region of Buenos Aires (AMBA), Argentina.¹

The AMBA provides a particularly informative setting for studying the distributional effects of public transport subsidies, as its current system combines multiple subsidy schemes (see Table 1). First, a universal subsidy keeps regulated fares below cost-recovery levels for all users by compensating operators for the gap between fares and service costs. Second, a targeted subsidy (the Social Tariff -ST-) grants additional fare discounts to specific vulnerable groups, including pensioners, beneficiaries of social assistance programs, and domestic workers. Finally, the Integrated Tariff (IT) provides automatic discounts for multi-stage trips within a two-hour window, applying to all users regardless of their eligibility for the ST.² Taken together, these schemes result in a mixed subsidy structure that combines universal and targeted components, raising the question of how the benefits are distributed across income groups.

The current subsidy scheme has the distinctive feature of emerging gradually through a sequence of policy reforms. Public transport subsidies have been in place since 2002, when a deep economic and social crisis led the national government to regulate fares and compensate operators in order to protect household incomes (Serebrisky *et al.*, 2009). Initially, subsidies were implemented primarily through supply-side transfers to operators, allowing the government to maintain fares at uniformly low levels for all users. During this early phase, subsidies therefore operated largely in a universal manner, as all passengers faced fares well below cost-recovery levels. A major institutional innovation occurred in 2009 with the rollout of the SUBE electronic ticketing system, which enabled the implementation of targeted fare discounts automatically and at scale. Building on this infrastructure, the ST was introduced in December

¹AMBA is a geographical area that includes the Autonomous City of Buenos Aires and its surrounding areas, covering 40 municipalities in the Province of Buenos Aires. It spans 13,285 km² and, according to the 2022 census, has approximately 14 million inhabitants, representing 37 percent of Argentina’s total population. See Figure A1 in the Appendix.

²In addition, a student fare subsidy (*boleto estudiantil*) has been in place since the late 1980s (Law 23,673, 1989). This program provides free or heavily subsidized public transport trips to students, typically up to a fixed monthly limit, and is primarily targeted to students attending public educational institutions.

2012, granting a 40 percent fare discount to specific low-income or socially vulnerable groups.³ Under the ST, eligible users do not receive a monetary transfer or a credit to their fare card. Instead, the subsidy operates through a reduced fare charged at the point of payment.⁴ In 2016, the ST was expanded and renamed the Federal Social Tariff, and its discount increased to 55 percent. In 2018, the IT was introduced, providing automatic discounts for multi-stage trips within a two-hour window. Specifically, the first trip is paid in full, the second receives a 50 percent discount, and subsequent trips receive a 75 percent discount, for up to five trips. As a result, users may face different effective fares depending on whether they benefit from the ST, the IT, both schemes simultaneously, or neither.

Beyond its institutional evolution, this subsidy regime is also characterized by its fiscal magnitude and structural composition. Initially modest (0.2 percent of GDP in 2002), subsidies expanded rapidly to reach 1.4 percent of GDP by 2015. Despite subsequent attempts at rationalization, they have remained substantial: in 2023, transfers to buses, suburban trains, and subways totaled USD 4.5 billion (0.7 percent of GDP), with about 65 percent directed to bus services and nearly 88 percent allocated to the AMBA. This has generated significant fiscal pressures, reflected in low cost-recovery rates (around 27 percent in the AMBA by mid-2024) and a high reliance on national government financing, which currently covers roughly 65 percent of total subsidies in the region.⁵

From an analytical perspective, the system combines supply-side subsidies that reduce fares for all users with demand-side instruments that target specific groups. By mid-2024, the minimum bus fare paid by users without ST was approximately USD 0.30, compared to an estimated average cost of USD 1.5 per trip. Targeted discounts such as the ST are delivered directly at the point of payment, while the resulting revenue gap is compensated through transfers to operators. This coexistence of universal and targeted instruments is central to understanding the distributional effects of transport subsidies analyzed in this paper.

To conduct the distributional analysis we rely on multiple data sources. Specifically, we combine data from the Encuesta de Movilidad Domiciliaria (ENMODO) and the Encuesta Permanente de Hogares (EPH). The ENMODO offers insights into the population’s transport

³Eligible users include retirees and pensioners; beneficiaries of the Universal Child Allowance (AUH) and Pregnancy Allowance (AUE); domestic workers; war veterans; recipients of unemployment insurance, employment-training, and productive-development programs; non-contributory pension holders; and small self-employed workers under the simplified tax regime. Access to the ST requires a registered SUBE card, allowing the discount to be applied directly at the point of payment.

⁴The resulting revenue shortfall for operators is subsequently compensated through supply-side transfers from the government, calculated on the basis of operational indicators such as the number of passengers transported and service kilometers within a regulated cost framework.

⁵Argentina is a federal country with four levels of government: national, provincial (23 provinces and the Autonomous City of Buenos Aires), and over 2,300 local governments (Porto & Puig, 2023).

usage patterns, while the EPH provides information on income distribution. Additionally, we incorporate administrative data from the SUBE system. We conduct a distributional analysis using the standard “benefit-incidence analysis” (van de Walle, 1998; Demery, 2000; Bourguignon & Pereira da Silva, 2003; Giuliano *et al.*, 2020). In a nutshell, this methodology follows three main steps. First, we classify the unit of analysis (i.e., bus users) into socioeconomic groups according to a welfare indicator (i.e., quintiles of per capita income). Second, we estimate the distribution of short-distance urban transport subsidy beneficiaries among quintiles. Specifically, beneficiaries are those who use urban bus transport in AMBA, considering whether they integrate (i.e., make trips of more than one stage) and whether or not they benefit from the ST.⁶ As in Börjesson *et al.* (2020), the subsidy is determined as the difference between the fare paid by users and the average operating cost of each trip. Finally, we allocate subsidies according to the distribution of beneficiaries. We analyze both absolute and relative distributional incidence, computing concentration curves and standard distributional indicators. In addition, we assess exclusion errors by identifying vulnerable populations not covered by the ST scheme, as well as inclusion errors arising from ST benefits received by non-vulnerable users. We also explore the role of public financing and the potential distributional effects of fare increases.

The results indicate that users with ST account for approximately 20 percent of the total user base. This implies that the majority of users and trips belong to the non-ST group, which receives a general flat subsidy. The ST is pro-poor, meaning that the number of beneficiaries decreases as higher income quintiles are considered. However, due to its design, the ST groups together heterogeneous beneficiary groups, including recipients of social assistance programs targeted to low-income households (such as families with children or unemployed household heads) and pensioners. As a result, while beneficiaries of social programs are concentrated at the lower end of the income distribution, pensioners are more prevalent in middle- and higher-income quintiles. This compositional feature weakens the pro-poor targeting of the ST and introduces an inherent tension in its distributive impact. For any user group, the proportion of income spent on buses decreases as higher income quintiles are considered. While the subsidy provided through the ST is distinctly pro-poor, the general flat subsidy, although favoring wealthier users, is also progressive. Taken together, the subsidy schemes are progressive overall, but they exhibit significant targeting shortcomings, with a disproportionate share of benefits accruing to higher-income users, largely driven by the dominance of the general flat subsidy. Accounting for financing further weakens the redistributive impact of bus subsidies, and may even reverse it under less progressive financing schemes. These findings underscore the importance of jointly considering subsidies and their financing in distributional analyses, as ignoring the latter may lead to an overestimation of their redistributive effects.

⁶Following standard practice in the benefit-incidence literature, we assume that users are the final beneficiaries of public transport subsidies (Asensio *et al.*, 2003).

Our paper provides a new applied economic analysis of a transport policy that has been in place for two decades in Argentina and is currently undergoing reform. To the best of our knowledge, no previous study has examined the distributional effects of public transport subsidies in Argentina as comprehensively as this one. Moreover, the analysis is timely and relevant for policymaking. Argentina is currently under an agreement with the International Monetary Fund (IMF) to reduce the fiscal deficit, with the revision of subsidies to public services being a key component of this agenda. Beyond the Argentine case, and as discussed in Section 2, the paper contributes to a still limited empirical literature on the distributional incidence of public transport subsidies, whose effectiveness and welfare implications remain topics of debate and empirical investigation, particularly in cities of the Global South (Guzman *et al.*, 2025). In many of these contexts, governments rely on public transport subsidies to balance affordability objectives with fiscal constraints. For example, Colombia introduced a means-tested fare subsidy in 2014 that grants discounted trips to low-income individuals through personalized smartcards (Gómez-Lobo *et al.*, 2022). In Brazil, the long-standing *Vale Transporte* program provides transit vouchers to formal-sector workers whose commuting costs exceed a fraction of their wages, although its distributional performance is limited by the exclusion of informal workers (Gómez-Lobo *et al.*, 2025). These experiences illustrate a broader policy dilemma faced by many urban transport systems in developing economies: while subsidies are often justified on equity and accessibility grounds, their effectiveness and welfare implications remain subject to debate. In this context, understanding how different subsidy schemes translate into actual distributional outcomes is critical for designing policies that reconcile equity goals with fiscal sustainability.

The remainder of the paper is organized as follows: Section 2 situates this study within the related literature and further contextualizes its contribution. Section 3 outlines the data and methodology employed. Section 4 presents the main distributional findings, including the role of public financing and a discussion of potential reforms. Finally, concluding remarks are provided in Section 5.

Table 1: Urban bus subsidy schemes in the AMBA

Subsidy scheme	Type	Year	Target groups	Discount structure
General fare subsidy	Universal	2002	All users	Regulated fares below cost-recovery; operators compensated via supply-side transfers
Social (ST)	Tariff	Targeted (2016 exp.)	Pensioners and retirees; AUH/AUE beneficiaries; domestic workers; unemployment insurance recipients; non-contributory pensions; small self-employed workers	40% fare discount (55% after 2016)
Integrated Tariff (IT)	Universal	2018	All users making multi-stage trips within a two-hour window	2nd trip: 50%; subsequent trips: 75% (up to five trips)

Source: Own elaboration based on official regulations.

2 Related literature

This paper contributes to the literature on the distributional effects of subsidies to urban public transport. Although the literature on this topic remains relatively limited, the available evidence generally suggests that these subsidies tend to benefit lower-income households. At the same time, important exceptions arise, particularly when subsidies are poorly targeted or when eligibility criteria exclude vulnerable groups. Table 2 summarizes selected contributions in this literature.

A first notable feature is that the literature is largely concentrated in European contexts, with Spain being one of the most extensively studied cases. [Asensio *et al.* \(2003\)](#) finds that urban public transport subsidies in Spain are progressive, as their relative weight in household income declines with income. Focusing on Madrid, [Bueno Cadena *et al.* \(2016\)](#) show that public transport usage is higher in lower-income neighborhoods, even when controlling for accessibility, supporting the idea that universal subsidies can have progressive effects. However, more recent contributions highlight important limitations in targeting. [Arranz *et al.* \(2019\)](#) analyze a fare subsidy policy for young users in Madrid and find that, while the policy increases accessibility for low-income households, the main welfare gains accrue to middle- and upper-middle-income groups, pointing to imperfect targeting. Similarly, [Arranz *et al.* \(2022\)](#) examine subsidies for the elderly and show that, although the policy benefits low-income individuals, it also generates significant gains for higher-income households, indicating leakage toward non-target groups. Overall, the evidence for Spain points to a broadly progressive pattern of public transport subsidies, but also underscores the presence of leakages and coverage limitations that may weaken their redistributive impact.

In the Paris Region, [Bureau & Glachant \(2011\)](#) examine the distributional impacts

of reduced public transport fares and find that such policies produce fairly uniform benefits across income groups. However, the gains represent a larger share of income for the poorest individuals, making the policy progressive. In Germany, [Tscharaktschiew & Hirte \(2012\)](#) find that the equity effects of public transport subsidies depend critically on both user characteristics and the financing mechanism. In particular, non-working households benefit the most, while high-skilled workers may experience net losses under income tax financing. In Stockholm, [Börjesson *et al.* \(2020\)](#) find that public transport subsidies are mildly progressive, largely due to discounts for students and retirees and lower usage by individuals in the highest income quintile. However, the progressivity is weak, as subsidies are distributed relatively equally across a wide range of income groups.

For the LAC region, evidence is particularly limited, with results available for only a few countries. In Bogotá, Colombia, [Guzman & Oviedo \(2018\)](#) study a pro-poor public transport subsidy scheme designed to alleviate the financial burden on poor households. Interestingly, Bogotá employs a national social policy targeting mechanism, SISBEN, which allows planners to classify beneficiaries and allocate subsidies. This system shares notable similarities with Argentina’s ST, as it considers various socioeconomic characteristics of individuals and households to generate a score that serves as a proxy for poverty. The subsidy scheme in Bogotá (as well as some alternative scenarios for increased coverage) is progressive, improving accessibility and equity for those benefiting from the subsidies. In Brazil, [Gómez-Lobo *et al.* \(2025\)](#) analyze the *Vale Transporte* policy, which requires formal sector employers to provide workers with public transport vouchers for commuting. Although the scheme is intended to support lower-wage workers, its eligibility criteria exclude a large share of low-income individuals employed in the informal sector. As a result, the subsidy is poorly targeted and often regressive, with benefits accruing disproportionately to middle- and upper-middle-income households. This evidence highlights how targeting based on formal employment can fail to reach the most vulnerable populations in contexts with high labor informality.

In Argentina, [Serebrisky *et al.* \(2009\)](#) state that between 2002 and 2006, supply-side subsidies in AMBA were regressive, with middle- and high-income households receiving the largest share. This conclusion builds on the findings of [Bondorevsky \(2007\)](#), which demonstrate that subsidies are primarily concentrated among higher-income groups. However, without comparing this concentration to the Lorenz curve, strict claims about regressivity are unwarranted; if any judgment about targeting can be made, it would likely suggest a bias favoring relatively wealthier users (i.e., absolute incidence or targeting). [Lakner *et al.* \(2016a\)](#) confirm this presumption, showing that over 50 percent of individuals in the bottom four deciles do not receive the subsidy, while many in the top deciles do. This lack of progressivity is attributed to eligibility criteria, particularly the inclusion of all retirees, which may not align with effective means-testing in Argentina. In this context, this paper deepens the understanding of

Argentina’s case. Methodologically, it improves the estimation of travel patterns by using the ENMODO survey, which allows for a more accurate measurement. Additionally, it captures the effects of the ST and the IT policies, which were absent in prior literature. In terms of results, our paper highlights persistent shortcomings in the targeting of transport subsidies in Argentina.

Beyond its specific focus, this paper also contributes to the broader understanding of subsidy policies for public services in Argentina. While subsidies to residential energy consumption (i.e., electricity and gas) have been extensively studied, contributions on transport subsidies are limited. Interestingly, studies on energy subsidies reveal patterns consistent with those observed in our paper: subsidies, though progressive, tend to favor wealthier groups in absolute terms ([Lustig & Pessino, 2013](#); [Puig & Salinardi, 2015](#); [Lakner *et al.*, 2016a](#); [Hancevic *et al.*, 2016](#); [Giuliano *et al.*, 2020](#); [Bertín *et al.*, 2024, 2025](#)).

Table 2: Selected literature on the distributional incidence of public transport subsidies

Study	Case Study	Methodology	Data	Main findings
Asensio et al. (2003)	Spain	Two-stage model (car ownership and PT expenditure)	Household survey	PT subsidies are progressive, but the redistributive effect is modest; progressivity increases with city size.
Serebrisky et al. (2009)	Multiple cities (Buenos Aires, Mexico City, Santiago, Mumbai)	Distributional incidence analysis	Household surveys	PT subsidies are generally poorly targeted; supply-side subsidies tend to be neutral or regressive, while demand-side schemes perform better but often remain insufficient to improve income distribution.
Bureau & Glachant (2011)	Paris Region	Distributional incidence analysis	Global Transport Survey	PT subsidies are progressive, with fairly uniform monetary gains across users; residential location matters more than income in shaping distributional outcomes, and speed improvements tend to benefit higher-income individuals more.
Tscharaktschiew & Hirte (2012)	German metropolitan area	Spatial urban CGE model	Multiple sources	Distributional effects depend on policy design and funding; reducing transit fares improves welfare for most groups, especially low-income and non-working households, while some high-skilled workers may lose under income tax financing.
Bueno Cadena et al. (2016)	Madrid	Two-stage model (travel pass usage and determinants)	Mobility survey	PT subsidies are progressive; lower-income neighborhoods exhibit higher travel pass usage, even when controlling for accessibility.
Lakner et al. (2016b)	Argentina	Distributional incidence analysis	Household survey	Targeting limitations reduce progressivity of PT subsidies, as benefits leak to middle- and upper-income households.
Guzman & Oviedo (2018)	Bogotá	Distributional incidence analysis	Mobility survey	Means-tested fare subsidies are progressive and improve accessibility.
Arranz et al. (2019)	Madrid	Difference-in-differences	Household survey	Fare subsidy for young users increases accessibility for low-income households, but most welfare gains accrue to middle- and upper-middle-income groups; no significant effects are found for the richest households.
Börjesson et al. (2020)	Stockholm	Distributional incidence analysis	Cross-sectional travel survey	PT subsidies are mildly progressive; top-income groups receive lower benefits due to fewer trips, while similar usage across other groups leads to limited redistributive impact.
Arranz et al. (2022)	Madrid	Regression discontinuity design	Household survey	Elderly-targeted subsidies benefit low-income groups but also generate significant gains for higher-income households, indicating imperfect targeting.
Gómez-Lobo et al. (2025)	Brazil	Distributional incidence analysis	Household survey	PT subsidies are poorly targeted and mostly regressive; limited progressivity arises from eligibility restricted to formal workers, excluding many low-income individuals.

Source: Authors' elaboration based on cited sources.

3 Methodology and data

The classification of bus users into socioeconomic groups requires integrating multiple micro-level data sources. To characterize the socioeconomic distribution of the population, we use the Encuesta Permanente de Hogares (EPH), Argentina’s primary household survey conducted by the National Institute of Statistics and Census (INDEC). The EPH is a continuous household survey that collects detailed information on demographic characteristics, labor market participation, income sources, and living conditions of individuals and households.⁷ The survey is conducted on a quarterly basis and covers the population residing in urban agglomerations across the country.⁸ Since our analysis focuses on the AMBA, we restrict the EPH sample to individuals residing in this region. For this paper, we use the waves corresponding to the first and second quarters of 2024.⁹

In this paper, the EPH plays two main roles. First, it provides the income distribution used to classify individuals into quintiles of per capita household income.¹⁰ Second, the survey includes information that allows us to identify potential beneficiaries of the ST, such as pensioners, domestic workers, and beneficiaries of social assistance programs. These characteristics are used to approximate eligibility for the ST scheme in the empirical analysis.

While the EPH provides detailed information on income and socioeconomic characteristics, it does not contain information on travel behavior. To characterize mobility patterns, we rely on the Encuesta de Movilidad Domiciliaria (ENMODO), a household travel survey that collects detailed information on daily travel behavior, including the number of trips, trip purposes, transport modes, travel times, and distances. The most recent wave available for AMBA was conducted in 2018 and provides a representative snapshot of mobility patterns in the metropolitan area.¹¹

⁷The EPH includes a wide range of variables covering demographic characteristics (age, gender, education, household composition), labor market status (employment, unemployment, occupation, sector of activity), and income from multiple sources. Income variables include earnings from the main occupation, secondary occupations, pensions, social transfers, and other non-labor income sources. These components allow the construction of household income aggregates such as total household income and per capita household income, which are widely used to measure income distribution and poverty in Argentina.

⁸The structure of the EPH dataset includes two main files: a household-level dataset and an individual-level dataset. Each household and its members can be linked through unique identifiers, allowing researchers to reconstruct household composition and socioeconomic characteristics.

⁹Using two consecutive quarters allows us to smooth potential seasonal effects in income reporting, particularly those associated with the payment of the annual bonus (“aguinaldo”), which may otherwise introduce short-term distortions in measured household income.

¹⁰We create quintiles of individuals ordered by per capita household income. We rely on the income directly reported in the survey, without applying corrections for underreporting. Existing correction methods for Argentina remain imperfect and may introduce additional distortions. For a discussion of this issue, see [Gasparini et al. \(2012\)](#).

¹¹The ENMODO dataset is organized into four main modules: households, individuals, trips, and trip

In this paper, ENMODO is used to characterize the mobility behavior of individuals, particularly the frequency and structure of public transport trips. Since ENMODO contains detailed travel information but lacks information on household welfare,¹² while EPH contains detailed income information but no mobility data, the two datasets are combined using a statistical matching procedure. Specifically, individuals in ENMODO are matched with observationally similar individuals in the EPH using a set of common demographic and socioeconomic characteristics. The matching is implemented using the `dmatch` routine in Stata. This procedure allows us to impute the income distribution from the EPH to the mobility patterns observed in ENMODO, thereby enabling the estimation of the distributional incidence of transport subsidies across income groups. Descriptive statistics for the main variables used in the matching procedure are reported in Appendix Table A1. Overall, the distributions of the key demographic and socioeconomic variables are broadly comparable across the two surveys, which supports the implementation of the statistical matching procedure.

For each individual, we impute the following: the number of daily trips made¹³; the purpose of the trips; the frequency of each trip per week; the number of stages; the duration (in minutes); and the distance traveled (in kilometers). For trips involving more than one stage, all stages are made by bus.¹⁴ Once bus users, trips, and income distribution are harmonized into a common sample, we classify users into different groups based on the tariff schemes available for public transport. First, we identify users eligible for the ST (i.e., Users with ST). Following Giuliano *et al.* (2020), we use survey questions corresponding to eligibility criteria (e.g., pensioners) or proxies when eligibility is not directly specified in the survey (e.g., beneficiaries of AUH or specific social programs like PROGRESAR and Potenciar Trabajo). Second, we identify students eligible for the student fare.¹⁵ Finally, we classify other users who do not benefit from any targeted transport subsidies (i.e., Users without ST).

Mobility patterns and the distribution of user types are compared with administrative records from the SUBE system. Mobility data is also combined with fare information (i.e., the prices paid by users) to estimate bus-related spending. This includes fares under the IT scheme. As shown in Figure A2 in the Appendix, fares vary by distance segment. For the analysis, we use stages. The household module contains information on housing characteristics and household composition. The individual module includes demographic and socioeconomic characteristics of household members, many of which overlap with variables available in the EPH (such as age, gender, education, employment status, and household composition). The trips module records all trips made by individuals during the reference day, including information on trip purpose, origin and destination, travel duration, and transport mode. Finally, the stages module provides a more granular description of each segment of a trip, allowing the identification of multimodal journeys and transfers between transport modes.

¹²At least in the databases available for public use, since there is one question in the survey questionnaire. Specifically, in the household module, the total income (from all sources) of the household is asked.

¹³Trips are restricted to a maximum of four per day, as they account for 98.22 percent of the total bus trips.

¹⁴Trips are restricted to a maximum of four stages, as they account for 99.83 percent of the total bus trips.

¹⁵See footnote 2.

fares in effect in April 2024, which were valid for most of the period covered in the paper. Since information on the distance of each trip is available, fare variability across trips is explicitly accounted for when estimating users’ transport expenditures. To calculate the subsidy received by users, we rely on the Technical Tariff (TT), which reflects the regulated average cost of providing a bus trip within the fare-setting framework.¹⁶ The subsidy is calculated as the difference between the TT and the fare paid by the user (Börjesson *et al.*, 2020), and we assume that the user is the final beneficiary of the subsidies (Asensio *et al.*, 2003). Information on fares and the TT is sourced from the Secretary of Transportation, part of the Ministry of Economy.

An important clarification applies here: the subsidies we estimate include those for ST, IT, their combined effects, and the general flat subsidy for users without ST (see Table 1). Notably, we do not include subsidies for the *boleto estudiantil* (see footnote 2), and this omission is due to several reasons. First, students are allowed up to 50 free trips per month, meaning they pay no fare for transportation. Second, the financing of this subsidy, unlike the others, is managed by provincial governments rather than the national government. Third, this subsidy has existed for decades, predating both ST and IT, and is unlikely to undergo significant reform in the short term. Finally, and most importantly, existing literature consistently shows that primary and secondary students in public schools (who represent the majority of students in AMBA) are distributed in a pro-poor manner (Gasparini *et al.*, 2012). Consequently, this subsidy is already recognized as highly progressive.

For the distributional analysis, we rely on the standard “benefit-incidence analysis” (van de Walle, 1998; Demery, 2000; Bourguignon & Pereira da Silva, 2003; Giuliano *et al.*, 2020).¹⁷ We compute the distributional incidence of subsidies in both absolute terms (i.e., focalization: how much of the total subsidy is appropriated by each quintile?) and relative terms (i.e., progressivity: the percentage of the subsidy appropriated by each quintile in relation to the percentage of welfare —income— it represents). See Gasparini *et al.* (2012) for a more detailed

¹⁶System costs are calculated based on the resolutions from the Ministry of Economy, Secretary of Energy, which regulates these costs in Annex 1 (cost structure). See [here](#) for the last available resolution. The TT does not vary at the individual-trip level, but represents a system-wide average cost. As a result, using an average TT may imply that subsidies are overstated for multi-stage trips and understated for one-stage trips. This limitation mirrors the institutional design of the subsidy scheme, in which supply-side transfers are calculated on the basis of aggregate cost structures rather than marginal costs per trip. Moreover, since one-stage trips account for the vast majority of journeys and subsidy spending, this measurement choice does not affect the main distributional patterns documented in the paper.

¹⁷In this framework, household income is used solely as a welfare indicator to rank households in the income distribution. The analysis does not attempt to estimate the causal impact of transport subsidies on income. Instead, the monetary value of the subsidy is imputed to users and allocated across income groups. Because the subsidy operates through reduced fares rather than as a monetary transfer, it is not directly observed in household income in the survey data.

discussion of these concepts. In addition, we calculate standard distributional indicators. On the one hand, we compute the subsidy concentration coefficient, which measures the degree of concentration of benefits in the lower deciles of income distribution. A negative value indicates a pro-poor subsidy. That is, as poorer households receive a higher share of the subsidy, the absolute value of the concentration coefficient increases. On the other hand, we compute the Kakwani coefficient, which measures the difference between the subsidy concentration coefficient and the Gini coefficient of income before subsidies. Negative (positive) values represent a progressive (regressive) subsidy, and therefore a more equitable income distribution (Giuliano *et al.*, 2020). Finally, we also compute the subsidy concentration curves and compare them with the Lorenz curve (i.e., income concentration). This measure is relevant as it allows us to compare the results of this paper with the existing literature (Bondorevsky, 2007; Serebrisky *et al.*, 2009; Lakner *et al.*, 2016a; Gómez-Lobo *et al.*, 2022). Two key dimensions must be analyzed here: (i) whether the subsidy concentration curve lies above or below the perfect equality line (i.e., the 45-degree line), which indicates whether the subsidy is pro-poor or pro-rich, respectively; and (ii) whether it is, in turn, above or below the Lorenz curve, which reflects whether the subsidy is progressive or regressive, respectively.¹⁸

Several caveats regarding methodology and data should be considered when interpreting our results. First, the mobility patterns observed in ENMODO correspond to data collected in 2018, prior to the COVID-19 pandemic, while the income data used from the EPH correspond to 2024. As a result, the analysis combines mobility information and socioeconomic characteristics observed in different periods. While aggregate mobility levels may have changed following the pandemic, our analysis focuses on the cross-sectional distribution of public transport subsidies across socioeconomic groups rather than on aggregate levels of travel demand. The key identifying assumption is therefore that the relative socioeconomic profile of public transport users remains broadly stable over time. This assumption is plausible in the context of the AMBA, where public transport continues to be widely used across income groups, while remaining intensively used by lower-income households and captive riders with limited access to private vehicles.¹⁹ Second, the imputation of travel patterns relies on observable variables common to both surveys, which may raise concerns typical of matching procedures. The distributions of these variables are broadly similar across ENMODO and EPH (see Appendix Table A1), supporting the plausibility of the matching strategy. To further assess its validity, we compare the resulting distribution of users and ST beneficiaries with administrative data from the SUBE system. As shown later in the paper, this comparison reveals a high degree of

¹⁸It is important to note that while every pro-poor subsidy is progressive, the inverse is not necessarily true. A progressive subsidy can still be pro-rich (Gasparini *et al.*, 2012).

¹⁹Consistent with this assumption, the broader macroeconomic environment does not suggest a structural break between the two periods. Appendix Table A2 compares standard macroeconomic indicators for 2018 and 2024 and shows that key aggregates—such as economic activity, employment, inequality, and the real exchange rate—remain broadly comparable across both years.

consistency between both sources. Third, some ST-eligible users cannot be explicitly identified in the survey due to the absence of proxy variables. For example, Malvinas War veterans and beneficiaries of the universal pregnancy allowance (AUE) cannot be directly observed. However, these groups account for less than 1% of users and trips, so their exclusion is unlikely to materially affect the main results.

A final caveat concerns the assumption that the user is the ultimate beneficiary of the subsidies. This assumption is perhaps more straightforward for demand-side subsidies, such as targeted fare discounts, but is less clear-cut for supply-side subsidies channelled through operators. In the latter case, the incidence of subsidies depends on the extent to which cost reductions are passed through to users in the form of lower fares or improved service quality. If pass-through were incomplete, our estimates would overstate the benefits accruing to users and understate those captured by operators. However, given the highly regulated fare-setting framework in Argentina (where fares are administratively set and subsidies are explicitly designed to bridge the gap between regulated fares and operating costs) the pass-through to users is likely to be high. From a distributional perspective, our results should therefore be interpreted as capturing the intended incidence of the subsidy scheme.²⁰

4 Main results of the distributional analysis

4.1 Bus trips in ENMODO

The total universe of trips reported in ENMODO slightly exceeds 30 million. Naturally, this universe includes trips of all types (whether by public or private transport, and in one or several stages). The subset involving the use of public transport can be categorized as follows: (i) 8.5 million one-stage trips on public transport, including bus, train, and subway modes; (ii) 0.6 million trips in two or more stages that combine public and private transport; and (iii) 5.2 million trips in two or more stages that exclusively involve public transport.

This paper focuses on trips made exclusively by bus. ENMODO reports 7.6 million one-stage bus trips, 0.87 million two-stage bus trips, and 0.08 million three-stage bus trips. An analysis of the purposes of one-stage trips (Column [1] in Table 3) reveals a relatively balanced distribution: 36.2 percent are for human capital investment purposes, 28.1 percent are for labor-related reasons, while the remaining 35.7 percent are for recreation, social events, or other reasons.²¹ In terms of gender, women account for 61.4 percent of trips in the overall

²⁰For a discussion of efficiency and incentive implications of supply-side transport subsidies, see [Parry & Small \(2009\)](#), [Tscharaktschiew & Hirte \(2012\)](#), and [Basso & Silva \(2014\)](#).

²¹Human capital investment trips include study-related purposes, such as traveling to educational institutions

universe. This is much in line with what [Rivas *et al.* \(2019\)](#) documents for the LAC region. Approximately half of bus trips are taken with a frequency of five times per week and cover distances of less than 3 kilometers. Regarding duration, 52.3 percent of bus trips take less than 30 minutes.

Table 3, in Columns [2] to [4], also provides details about trips involving more than one stage. Notably, two-stage trips are primarily work-related. Regarding frequency, such trips are mostly weekly, with over 40 percent occurring five times per week. Distances tend to increase with the number of stages, as does the concentration of trips, correlating with longer durations. Multi-stage trips are therefore more common among those involving greater distances and extended travel times.

or accompanying household members to such centers. Labor-related trips include commuting to the workplace, job-related errands, and job searching.

Table 3: Description of bus trips by number of stages

	Stages			
	One	Two	Three	Four
	[1]	[2]	[3]	[4]
Total trips	7,597,321	870,980	85,804	2,134
Gender				
Male	38.6%	39.9%	40.1%	0.0%
Female	61.4%	60.1%	59.9%	100.0%
Age groups				
Less than 18	21.4%	10.4%	16.3%	0.0%
Between 18 and 60	66.7%	76.7%	76.3%	100.0%
More than 60	11.9%	12.8%	7.4%	0.0%
Trip purpose				
Investment in human capital	36.2%	24.0%	18.5%	23.5%
Labor	28.1%	44.3%	50.1%	76.5%
Entertainment, others	35.7%	31.7%	31.4%	0.0%
Weekly frequency				
Once	6.7%	6.6%	11.7%	0.0%
Two to Four Times	16.3%	19.9%	19.9%	46.0%
5 times	47.9%	42.3%	41.9%	54.0%
5+ times	4.4%	8.1%	7.1%	0.0%
Once every two weeks	24.7%	23.1%	19.4%	0.0%
Distance (Kms)				
Less than 3	47.6%	9.1%	6.1%	0.0%
Between 3 and 12	43.4%	56.5%	20.3%	23.5%
More than 12	9.0%	34.4%	73.6%	76.5%
Duration (minutes)				
Less than 30'	52.3%	9.8%	2.0%	0.0%
Between 30' and 60'	35.9%	37.6%	15.1%	0.0%
More than 60'	11.8%	52.6%	83.0%	100.0%

Source: Author's elaboration based on ENMODO 2018.

4.2 Bus users and trips in EPH

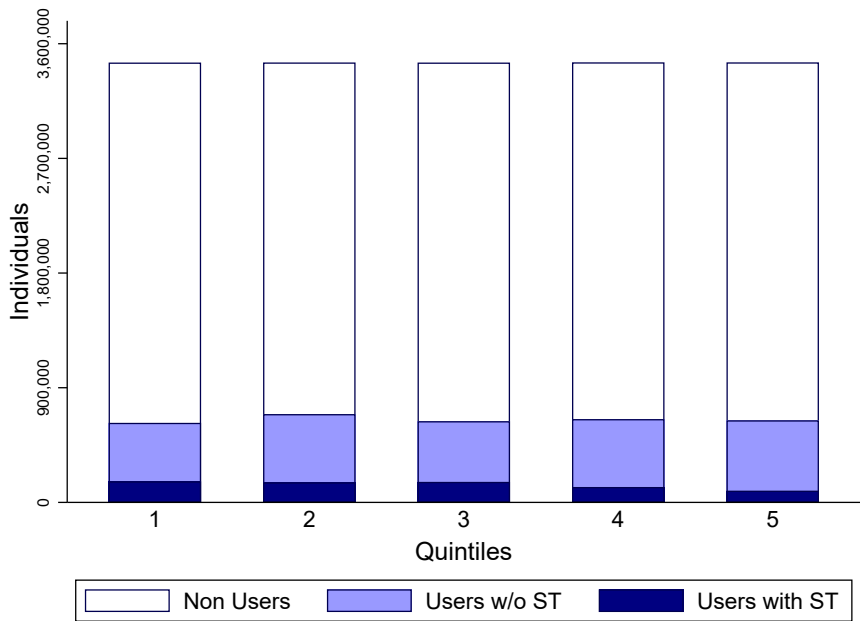
Approximately 17.2 million people live in AMBA. Of these, 3.2 million make bus trips involving one or more stages. Among these users, almost 0.8 million benefit from the ST. It is important to emphasize that of the total number of users, only 22.6 percent, on average, have access to the targeted subsidies under the ST. This share is consistent with what is indicated in the SUBE administrative records (see Figure A3 in the Appendix). Figure 1 illustrates the distribution of these users across income quintiles. The data show that the distribution of users, including those receiving the ST, is relatively uniform across the income distribution.

When analyzing users with ST, it is first important to note that the distribution identified in the microdata of the main groups of ST users is consistent with what is indicated in the SUBE administrative records (see Figure A3 in the Appendix). Figure 2 shows that the number of users with ST decreases with the level of welfare. This suggests a pro-poor distribution of the ST beneficiaries (i.e., there are more users with ST concentrated in the lowest quintiles). However, the different criteria with access to ST show different distributional characteristics. The beneficiaries of AUH and other social programs (i.e., others with ST) show a pro-poor distribution: 75.2 percent and 71.7 percent of the beneficiaries respectively belong to the 40 percent with the lowest income. On the other hand, 30.6 percent of pensioners are concentrated in the bottom 40 percent. This latter group represents 58.0 percent of all ST beneficiaries, while AUH beneficiaries represent 19.5 percent. This distribution is also aligned with the administrative records of the SUBE: the share of pensioners in the total of ST is around 58 percent and the corresponding share of AUH is close to 25 percent.

In addition to users with ST, there are other two groups that are relevant for the distributional analysis of the subsidies to bus transport. On the one hand, those attending educational institutions (i.e., students), who have access to other subsidy schemes that differ from the ST (i.e., “boleto estudiantil”). They represent almost 29.1 percent of the users and the distribution varies depending on whether the students are in public or private establishments (Figure 3). The former (second) follow a pro-poor (pro-rich) distribution. On the other hand, there are users who do not have access to ST subsidies and are not students. These account for almost half (48.2 percent) of the bus transport users in AMBA and are increasingly distributed with income level (Figure 3). When focusing on the share of users concentrated in the bottom 40 percent with the lowest income: 27.2 percent of users are covered by the ST; 31.1 percent are students; and 41.5 percent are excluded from any transport subsidy mechanism.

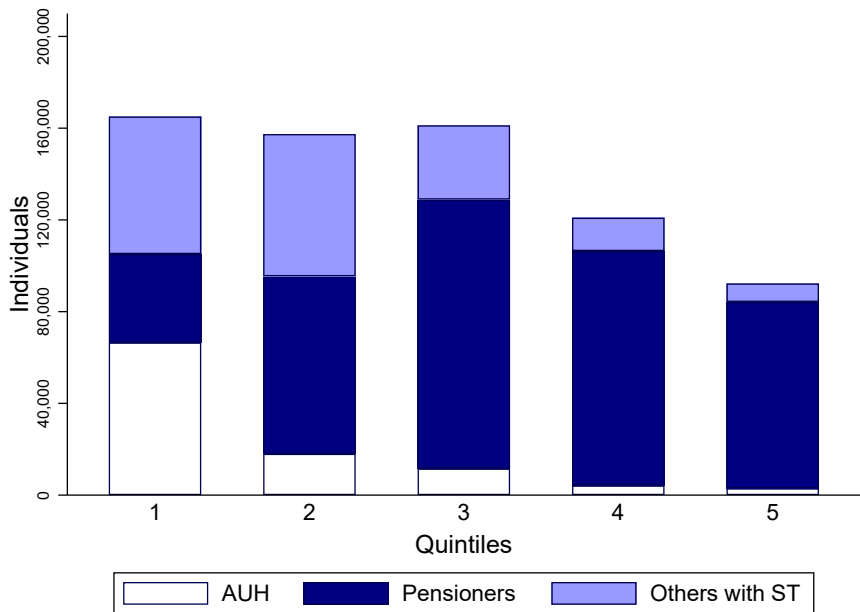
Figure 3 provides additional detail on the groups excluded from the ST. A relevant stylized fact for better targeting indicates that the group without any subsidies includes people with different characteristics: housewives, salaried workers (formal and informal), self-employed workers, and unemployed, among others. Each group is distributed in a certain way along the

Figure 1: Bus users in AMBA. Different types of users. By quintile of per capita family income



Source: own elaboration based on ENMODO 2018 and EPH 2024. Note: Users refer to individuals who make trips exclusively by bus. ST denotes the Social Tariff. All values are weighted by the population growth factor.

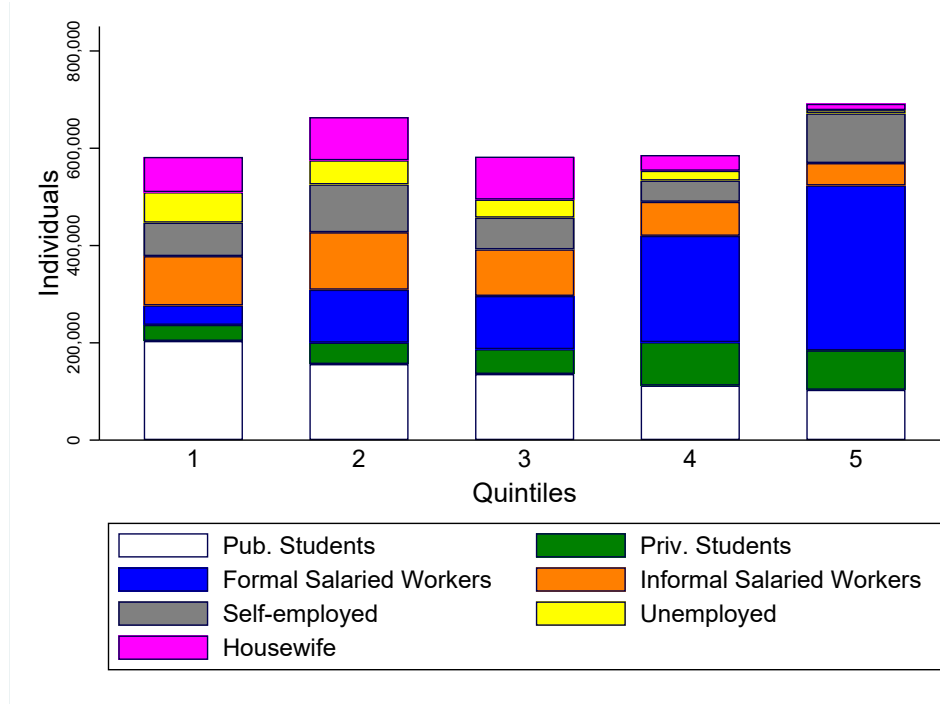
Figure 2: Bus users with ST in AMBA. Most relevant eligible groups. By per capita household income quintiles



Source: own elaboration based on ENMODO 2018 and EPH 2024. Note: Users refer to individuals who make trips exclusively by bus. ST denotes the Social Tariff. All values are weighted by the population growth factor.

welfare distribution. This issue, together with the possibility of identifying them in administrative records, is crucial for minimizing the exclusion error in the ST (Serebrisky *et al.*, 2009).

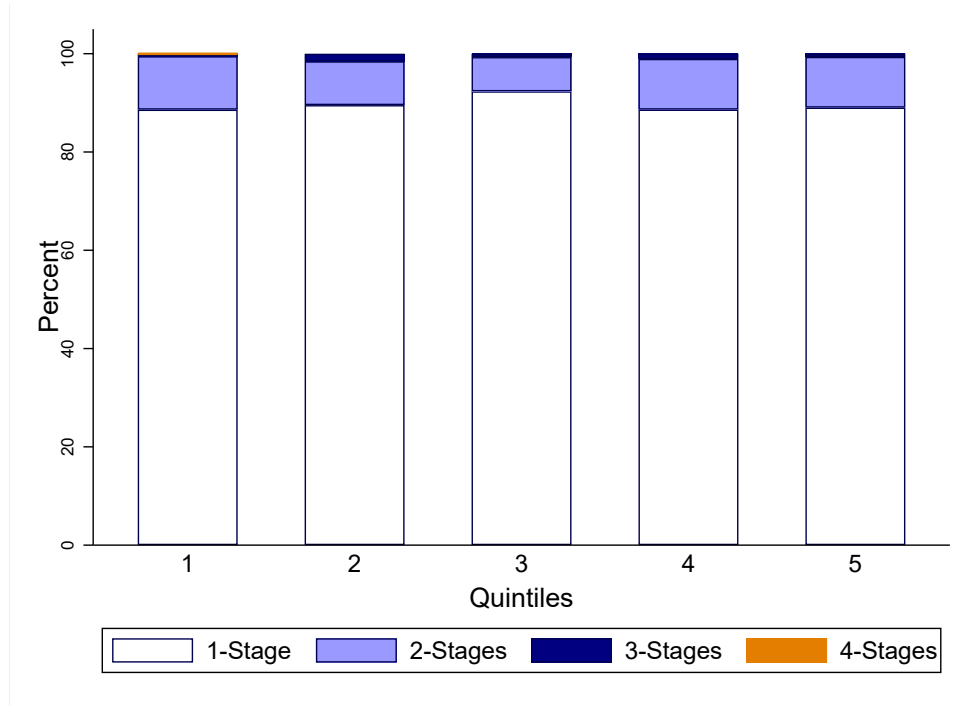
Figure 3: Bus users without ST in AMBA. Most relevant groups. By per capita household income quintiles



Source: own elaboration based on ENMODO 2018 and EPH 2024. Note: Users refer to individuals who make trips exclusively by bus. ST denotes the Social Tariff. All values are weighted by the population growth factor.

Finally, Figure 4 shows the distribution of trips. Naturally, and in line with what is observed in Table 3, about 90 percent of the trips are one-stage trips. The relevance of three- or four-stage trips seems to be negligible. Of the total number of one-stage trips, 21.5 percent are with ST; 49.4 percent with no social attribute; while the rest (28.9 percent) are made by students (not shown in the Figure). A very similar distribution applies to two-stage trips. Finally, Figure A4 in the Appendix shows the distribution of trips in levels for each group of users.

Figure 4: Trips in urban bus transport. AMBA. Main groups based on fare schemes. By per capita household income quintiles



Source: own elaboration based on ENMODO 2018 and EPH 2024. Note: All values are weighted by the population growth factor.

4.3 Budget share of spending on bus

Bus transportation in AMBA presents a strong distributional pattern, as the budget share decreases along the income distribution (Figure 5). Combining the trips with the fares applicable during the first half of 2024 (see Figure A2 in the Appendix), it is possible to estimate the expenditure on bus according to each pricing scheme. On average, a bus user spends 2.8 percent of their income on bus trips.²² This bus expenditure share is non-linear in distribution: a user from the lowest 20 percent of income spends 5.3 percent of their income, while a user from the highest 20 percent of income spends 0.9 percent. As [Rivas *et al.* \(2019\)](#) and [Gandelman *et al.* \(2019\)](#) note, low-income households are particularly affected by public transport prices. In addition, this stylized fact is consistent with [Falavigna & Hernandez \(2016\)](#), which measure public transport in Córdoba, the second-largest city in Argentina, after Buenos Aires: the poorest households proportionally spend approximately five times more than households in the top quintile.

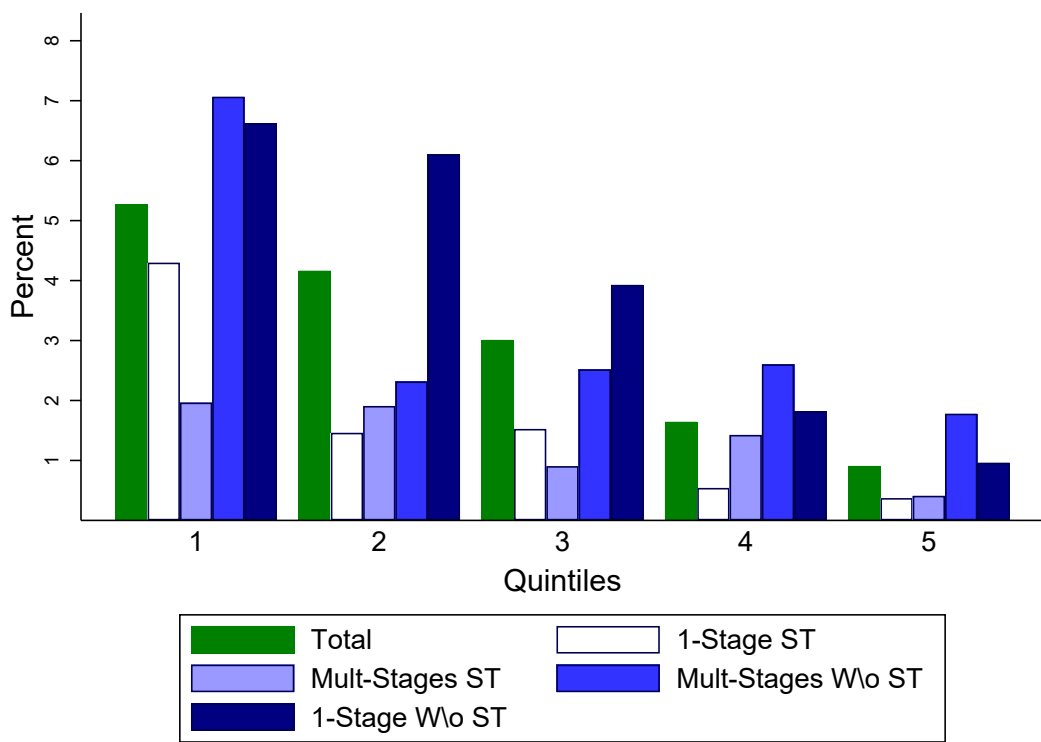
There are also differences between the budget share of users with and without the ST. Those with ST who do not integrate (i.e., make only one-stage trips) spend, on average, 1.8 percent of their income, and this share is non-linear in distribution: a user from the lowest 20

²²This is in line with what [Rivas *et al.* \(2019\)](#) document for the LAC region. All transportation services expenditures relative to total consumption expenditures are 4.5 percent and 5.2 percent for the “lowest” and “low” consumption segments, respectively.

percent of income spends 4.3 percent of their income, while a user from the highest 20 percent of income spends 0.4 percent.

Users with ST who do integrate spend, on average, 1.4 percent of their income; a user from this group belonging to the lowest 20 percent of income spends 2.0 percent, while a user from the highest 20 percent of income spends 0.4 percent. Users without ST who do not integrate spend, on average, 2.5 percent of their income, and this share is non-linear in distribution: a user from the lowest 20 percent of income spends 7.1 percent of their income, while a user from the highest 20 percent of income spends 1.8 percent. Finally, users without ST who do integrate spend, on average, 3.4 percent of their income; a user from this group belonging to the lowest 20 percent of income spends 6.6 percent, while a user from the highest 20 percent of income spends 1.0 percent.

Figure 5: Budget share of spending on urban bus transport. Main groups based on fare schemes. By per capita household income quintiles



Source: own elaboration based on ENMODO 2018, EPH 2024, and Ministry of Economy. *Note:* ST denotes Social Tariff. All values are weighted by the population growth factor.

4.4 Distributional incidence of subsidies

Figure 6 shows the distributional incidence of subsidies by quintiles. The bars reflect the absolute incidence. The broken line shows the relative incidence. Panel A shows the subsidies received by users who have a ST and make only one-stage trips (i.e., they do not integrate). These subsidies represent, in our estimates, 21 percent of the total. It can be observed that, of the total subsidy, the lowest-income quintile (highest-income quintile) concentrates approximately 30 percent (10 percent). Therefore, the subsidy is pro-poor and strongly progressive. Considering the standard distributional indicators, the concentration coefficient for these subsidies is -0.20 and the Kakwani index is -0.67 (not shown in the Figure). It is worth noting that the concentration coefficient for this type of subsidy in particular in Argentina is very much in line with what Börjesson *et al.* (2020) found for Stockholm. Panel B illustrates the case of users with the ST who make trips of more than one stage, and the distribution results remain consistent with the pattern described above. Here, the concentration coefficient is also -0.20 and the Kakwani index is also -0.67. These subsidies represent, in our estimates, 8 percent of the total.

Panels C and D depict the subsidies for users who do not have the ST, categorized by whether they make multi-stage or one-stage trips, respectively. Here operates the general flat subsidy. According to our estimates, the former subsidies represent 14 percent of total transport subsidies. The latter represent 57 percent of the total. Two notable patterns emerge. First, the targeting of these subsidies is concentrated on higher-income quintiles. Of the subsidies allocated to users who make one-stage trips (Panel D), the lowest-income quintile (highest-income quintile) concentrates approximately 12 percent (30 percent). Second, although less pronounced than in the case of the ST, the subsidies are still progressive. The concentration coefficient for subsidies in Panel C (D) is 0.17 (0.18) and the Kakwani index is -0.31 (-0.29).

Figure 7 illustrates the distributional effects of subsidies using their concentration curve and comparing it with the Lorenz curve (i.e., the income concentration curve).²³ The concentration curve (regardless of the case considered with respect to the ST and integration) is always located above the Lorenz curve, indicating the progressiveness of the subsidy. However, in relation to the line of perfect equality (i.e., 45° line), only the ST subsidy for one-stage trips lies above it (Panel A). This means that, at usual confidence levels, this is the only subsidy that can definitively be identified as well-targeted and pro-poor. At the other extreme, Panel D illustrates the opposite case for users without ST who do not integrate. At the usual confidence levels, this subsidy, while progressive, is markedly pro-rich.

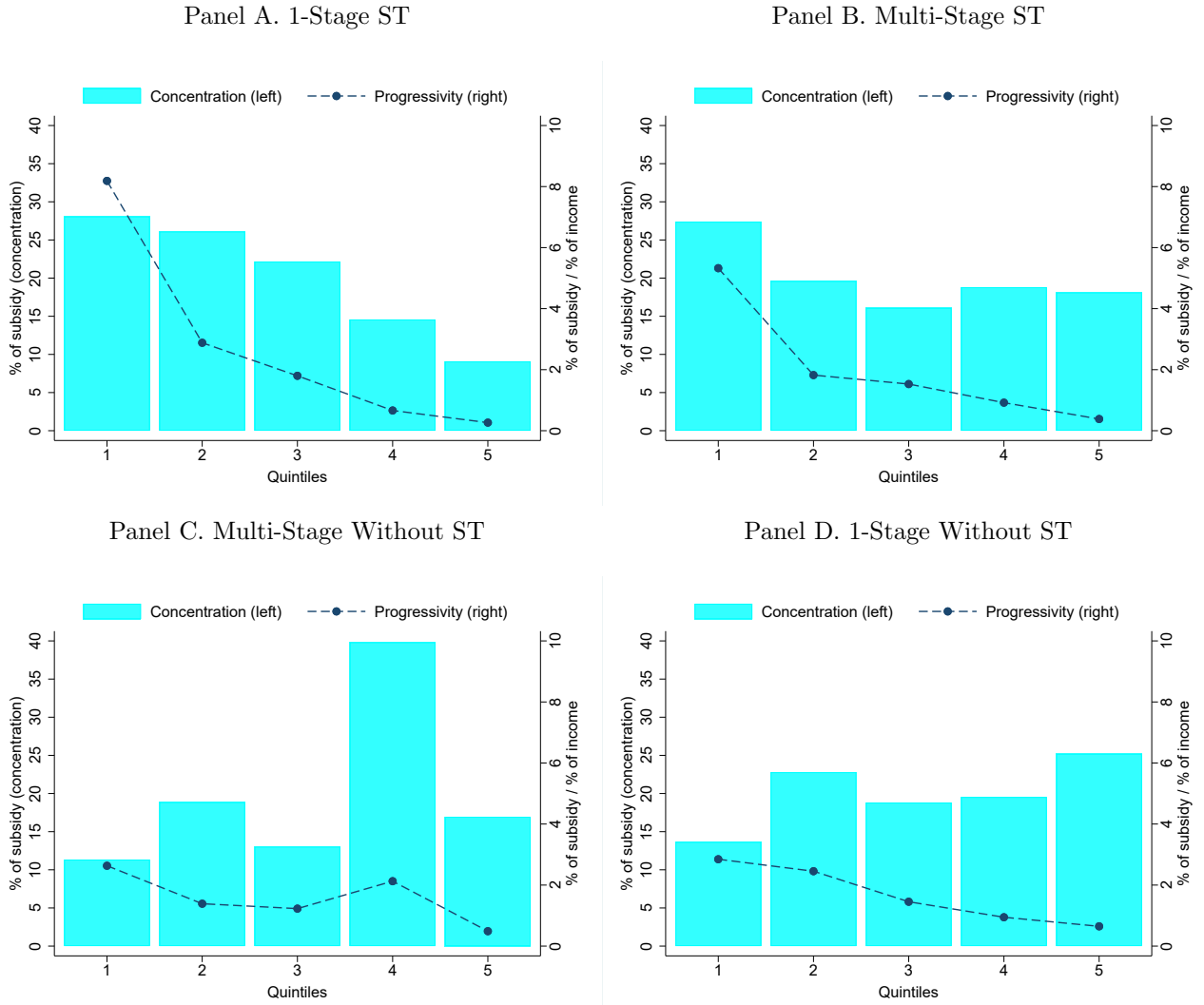
Finally, Figure 8 summarizes the aggregate subsidy policy: bus transportation subsi-

²³Lorenz curves have been widely used to examine the role of public transport on equity. See, for example, Delbosc & Currie (2011).

dies in the AMBA are progressive but pro-rich. This result is consistent with previous findings for Argentina (Serebrisky *et al.*, 2009; Lakner *et al.*, 2016a). The concentration coefficient for the overall subsidy policy is 0.07 and the Kakwani index is -0.40. This result arises from the interaction of two features of the current subsidy architecture. On the one hand, the ST is comparatively better targeted, as eligibility is linked to observable conditions of social vulnerability and its beneficiaries are more concentrated in the lower part of the income distribution. On the other hand, the bulk of public resources is allocated through a general flat subsidy that applies broadly across users, including groups that are increasingly represented in the middle and upper quintiles. As a result, even though both components are progressive in relative terms, the dominance of the untargeted subsidy generates substantial leakage toward better-off households and explains why the overall system remains pro-rich in absolute incidence.²⁴

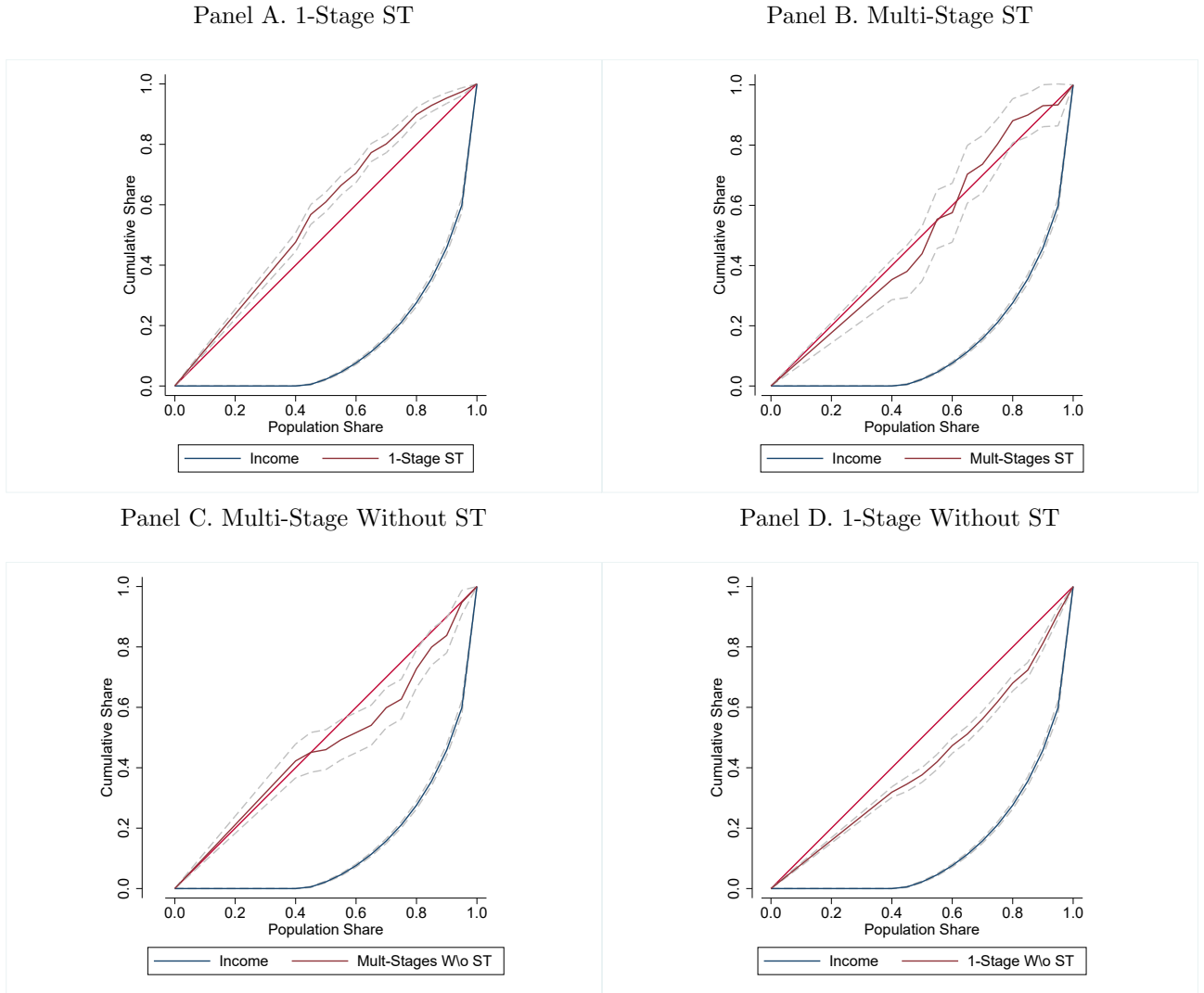
²⁴As remarked, our estimates do not include the student fare subsidy (“boleto estudiantil”). As shown in Figure 3, students represent approximately 29 percent of users, and those attending public schools (who account for the majority of student users) are strongly concentrated in the lower income quintiles. Consequently, including the student subsidy would likely reinforce the progressive component of the subsidy system rather than alter the main distributional patterns documented in the paper.

Figure 6: Distributional incidence of the subsidies to urban bus transport. By per capita household income quintiles. AMBA. In absolute and relative terms.



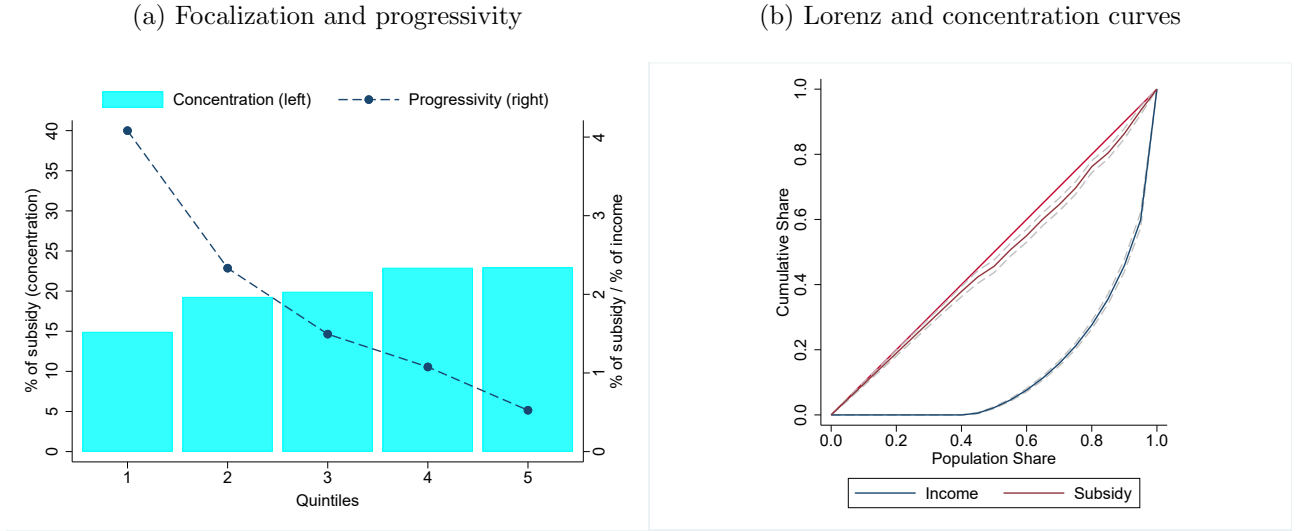
Source: own elaboration based on ENMODO 2018, EPH 2024, and Ministry of Economy. *Note:* ST denotes Social Tariff. All values are weighted by the population growth factor. Bars represent the share of total subsidies received by each income quintile (absolute incidence, left axis). The dashed line shows the ratio of the subsidy share to the income share of each quintile (relative incidence, right axis). Values above one indicate that the quintile receives a larger share of subsidies than its share of income (progressive), while values below one indicate the opposite.

Figure 7: Concentration and Lorenz curves for distributional incidence of the subsidies to urban bus transport in AMBA.



Source: own elaboration based on ENMODO 2018, EPH 2024, and Ministry of Economy. *Note:* ST denotes Social Tariff. All values are weighted by the population growth factor. Dashed lines represent 95% confidence intervals. The blue curve shows the Lorenz curve of income, while the red curve represents the concentration curve of the subsidy. The 45-degree line indicates perfect equality. If the concentration curve lies above (below) the Lorenz curve, the subsidy is progressive (regressive) in relative terms.

Figure 8: Distributional incidence of the subsidies to urban bus transport in AMBA.



Source: own elaboration based on ENMODO 2018, EPH 2024, and Ministry of Economy. Note: ST denotes Social Tariff. All values are weighted by the population growth factor. In Panel (a), bars represent the share of total subsidies received by each income quintile (absolute incidence, left axis). The dashed line shows the ratio of the subsidy share to the income share of each quintile (relative incidence, right axis). Values above one indicate that the quintile receives a larger share of subsidies than its share of income (progressive), while values below one indicate the opposite. In Panel (b), the blue curve shows the Lorenz curve of income, while the red curve represents the concentration curve of the subsidy. The 45-degree line indicates perfect equality. If the concentration curve lies above (below) the Lorenz curve, the subsidy is progressive (regressive) in relative. Dashed lines represent 95% confidence intervals.

4.5 The role of public financing

To further understand the distributional impact of transport subsidies in AMBA, we extend the analysis to consider their financing. While this exercise is not the core focus of the paper, it is informative for interpreting the overall distributional effects of subsidy policies. As emphasized by Musgrave (1964) many decades ago: “... [a]ny meaningful theory or policy in public finance must ultimately combine the issues posed by the two sides of the budget. This, indeed, is the cardinal principle of the economist’s view of public finance.” In practice, programs and taxes are often analyzed separately, but doing so may lead to misleading conclusions. A policy that appears progressive on the spending side may become much less so (or even regressive) once its financing is taken into account (Gasparini *et al.*, 2012).

To illustrate this point, we explore two alternative financing schemes under a balanced-budget assumption, whereby total tax revenues equal the total cost of transport subsidies. The first scheme assumes a tax proportional to income, while the second considers a lump-sum tax. These scenarios are not intended to replicate Argentina’s tax system in detail, but rather to provide transparent benchmarks that help gauge the sensitivity of distributional outcomes to different financing assumptions.

From an institutional perspective, these stylized financing schemes capture key features of Argentina’s tax structure rather than its full complexity. Public revenues rely heavily

on indirect taxation (most notably the value-added tax and turnover taxes at the subnational level) while personal income taxation plays a more limited role. As a result, the overall tax system is closer to proportional or mildly regressive than to strongly progressive (Felices *et al.*, 2016). In this context, proportional taxation can be interpreted as a reasonable approximation to average financing conditions, while lump-sum taxation provides a lower-bound benchmark for assessing distributional sensitivity.

Panel A in Figure 9 presents the net effect under proportional taxation, calculated as a share of income.²⁵ For instance, the poorest quintile receives an average of 1.12 percent of its income in subsidies but contributes 0.25 percent of its income through proportional taxation. In net terms, the average household in the poorest quintile gains 0.87 percent of its income (i.e., the overall effect), which is less than the gain from subsidies alone. This reduction in benefit is observed across all quintiles. Thus, when proportional financing is considered, the progressivity of transport subsidies is diminished.

Panel B in Figure 9 illustrates the net effect under lump-sum taxation. As expected, this form of taxation is regressive, leading to substantial changes in distributional outcomes. The poorest quintile contributes 1.52 percent of its income under a lump-sum tax. In net terms, the average household in this quintile loses 0.41 percent of its income (i.e., the overall effect), a marked reduction compared to the gain from subsidies alone. This pattern persists across most quintiles, with the largest relative reductions occurring among lower-income households. These results highlight the importance of considering both subsidies and their financing in distributional analyses (Bertín *et al.*, 2024). Ignoring the financing dimension could lead to an overestimation of the redistributive impact of subsidies.

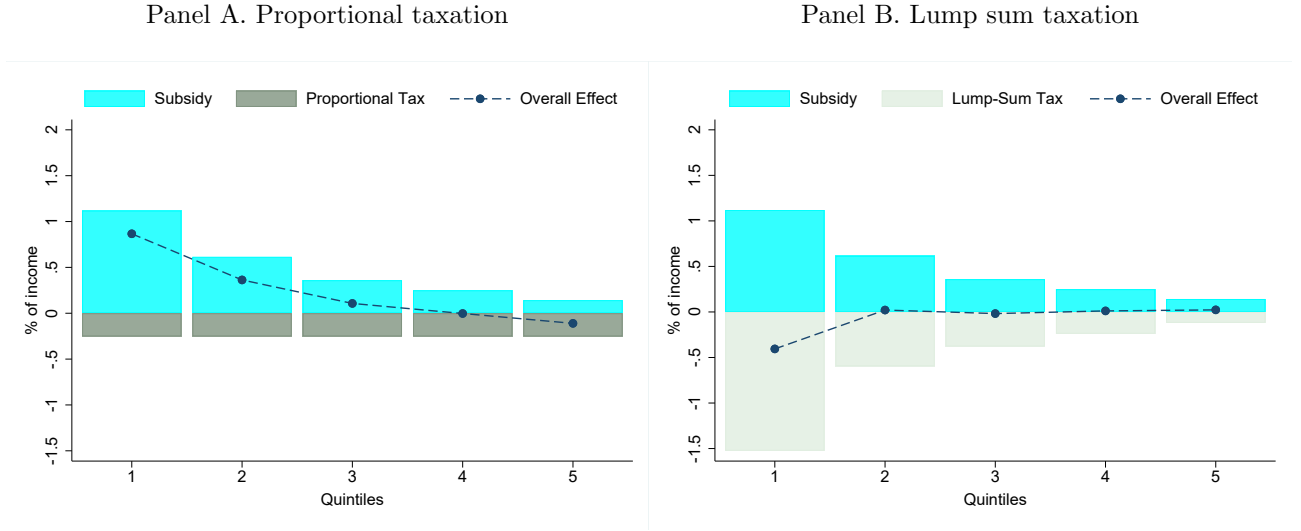
4.6 Further discussion on potential reforms

The current distributional results of subsidies raise concerns about their equity effects. To examine how the distributional impact of subsidies could potentially be adjusted, we explore a microsimulation of fare increases relative to the current situation. The analysis considers three scenarios in which fare increases are applied exclusively to users who do not qualify for the ST. These increases are set at 25 percent, 50 percent, and 100 percent, respectively, with the aim of reducing the general flat subsidy.

Before presenting the results, it is important to address some assumptions and limita-

²⁵Since the objective of this exercise is illustrative, we adopt simple and transparent metrics to assess the net distributional effects of transport subsidies under alternative financing assumptions. Other approaches—such as full fiscal incidence analyses based on disposable or consumable income (Lustig & Pessino, 2013)—are also valid, but would require a substantially richer modeling of the tax system, which lies beyond the scope of this paper.

Figure 9: Net distributional incidence of urban bus transport subsidies in AMBA when considering public financing. By quintiles of per capita income. In percentage of the household income



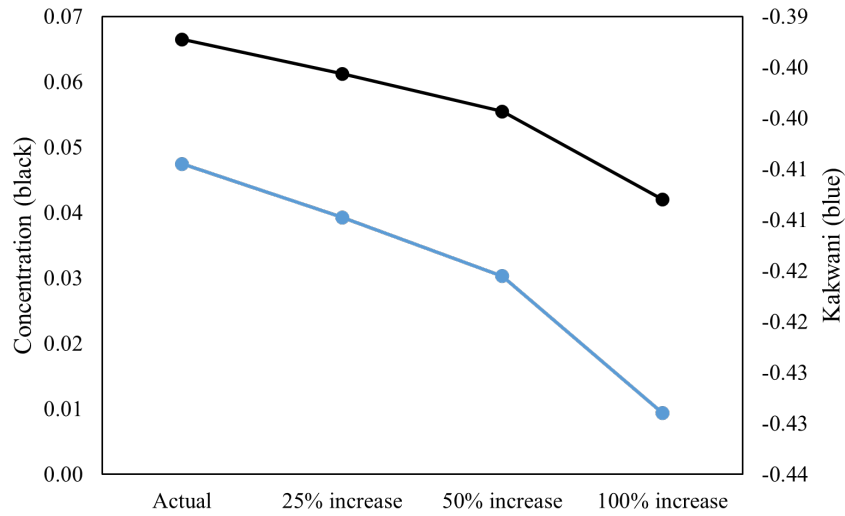
Source: own elaboration based on ENMODO 2018, EPH 2024, and Ministry of Economy. Note: All values are weighted by the population growth factor.

tions of this analysis. First, it is assumed that user's behavior remains unchanged despite price increases (Bureau & Glachant, 2011). While public transport demand is relatively inelastic, price increases of this magnitude are likely to induce second-order or substitution effects (e.g., modal shifts or changes in travel frequency). Therefore, the results presented here are rather limited to a static behavioral context. Second, it is assumed that fare increases do not lead to cost reductions for transport operators (Asensio *et al.*, 2003). While this may be a reasonable assumption in the short term, over the longer term, costs could decrease due to new investments enabled by higher revenue from increased fares.

With these caveats in mind, Figure 10 presents the concentration coefficients and Kakwani indices for each scenario (see also Appendix Figure A5 for the corresponding concentration curves). Although both targeting and progressivity improve under higher fare scenarios, the magnitude of these changes remains relatively limited, even under substantial fare increases. Moreover, the composition of subsidies changes only modestly. The share of general flat subsidies (i.e., subsidies for one-stage trips without ST) remains close to 50 percent of the total (not shown in the figure). This share is likely to decline further once behavioral responses are taken into account, implying that our estimates should be interpreted as an upper bound. At the aggregate level, total subsidies would be reduced by approximately 20 percent under the maximum fare increase scenario. This figure should be interpreted as a lower bound, as it does not incorporate potential reductions in demand. For context, doubling fares from their April 2024 levels would increase cost-recovery substantially: the minimum fare would cover about 38 percent of service costs, while the fare for the longest distance segment would cover

approximately 52 percent.

Figure 10: Distributional impacts of potential fare increases in urban bus transport. AMBA.
Concentration and Kakwani Indices



Source: own elaboration based on ENMODO 2018, EPH 2024, and Ministry of Economy. *Note:* All values are weighted by the population growth factor.

5 Discussion and concluding remarks

This paper provides new empirical evidence on the distributional effects of urban bus transport subsidies in the AMBA, Argentina. A key contribution is to evaluate the full subsidy architecture (combining universal fare support, targeted discounts, and integration mechanisms) and to show how their interaction ultimately shapes the overall distributive outcome.

Our results show that subsidies are progressive in relative terms, but not necessarily well targeted in absolute terms. This outcome reflects the coexistence of two very different subsidy instruments. On the one hand, the ST is comparatively more progressive and better aligned with social protection objectives, as its beneficiaries are more concentrated in the lower quintiles of the income distribution. On the other hand, the general flat subsidy embedded in regulated fares applies broadly across users and absorbs the bulk of fiscal resources. Because this universal component reaches users across the entire distribution, and accounts for a much larger share of beneficiaries and trips than the ST, the overall subsidy system turns out to be progressive but pro-rich. In other words, the targeted component improves incidence at the margin, but it is not large enough to offset the distributive consequences of the dominant untargeted scheme.

This interpretation is consistent with previous evidence on transport subsidies in the LAC region, where distributive performance depends critically on the quality of the eligibility

instrument. In particular, broad categorical criteria (such as extending benefits to all retirees regardless of income) may substantially weaken targeting performance. Our results for the AMBA are in line with this logic: while the ST improves incidence relative to the general subsidy, it still exhibits both inclusion and exclusion errors under a poverty-oriented interpretation of transport support. At the same time, vulnerable groups excluded from administrative registries, such as informal workers or individuals with unstable labor-market attachment, remain difficult to reach through conventional targeting mechanisms.

The comparison with the broader literature also shows that this tension is not specific to Argentina. Evidence from European settings suggests that public transport subsidies can improve the economic well-being of vulnerable households, while also generating gains for non-vulnerable groups when eligibility is based on broad demographic criteria (such as age) rather than income or socioeconomic conditions. This reinforces one of the main lessons of our paper: the distributive performance of transport subsidies depends not only on whether they are targeted, but also on how eligibility is defined and on the relative budgetary weight of targeted and untargeted components.

Although our analysis focuses on the AMBA, the trade-offs that emerge from this setting have broader relevance. First, there is an administrative trade-off: more refined targeting may reduce leakage, but it also raises the risk of exclusion errors when eligibility cannot be easily verified. Second, there is a political trade-off: universal or quasi-universal subsidies are easier to sustain politically, while more selective schemes may face resistance from groups that would lose benefits. Third, there is a fiscal trade-off: as our financing exercises show, the net redistributive effect of subsidies depends crucially on how they are funded. Once financing is taken into account, the progressive effect observed on the spending side may be substantially attenuated or even reversed under sufficiently regressive funding arrangements.

Our results also speak to a broader debate in the transport literature. Equity is only one possible rationale for subsidizing public transport. Efficiency arguments (such as scale economies in public transport provision -the Mohring effect- and the role of subsidies as a second-best instrument to address congestion and environmental externalities) may justify designs that differ from those preferred on redistributive grounds. In particular, if the objective is to induce substitution away from private car use, directing subsidies toward users with greater access to private alternatives may be more effective from an efficiency standpoint, even if such a design is less progressive. By contrast, if the objective is to relax transport constraints faced by low-income households in accessing jobs, education, or health services, tighter targeting becomes more compelling. The AMBA case therefore illustrates a broader point: subsidy systems that perform better in terms of redistribution are not necessarily those that maximize efficiency, and vice versa.

As with any empirical analysis, this study has several limitations that should be considered when interpreting the results. These are discussed in detail in the methodology section and relate primarily to data comparability, the imputation strategy, and the static nature of the policy simulations.

Overall, the evidence suggests that the main weakness of the current AMBA bus subsidy system is not the absence of a targeted instrument, but the overwhelming weight of the untargeted one. A more coherent reform strategy would therefore require not only expanding or refining the ST, but also revisiting the role of generalized fare subsidies, while explicitly considering the financing side and the trade-offs between equity, efficiency, and political feasibility. This is, in our view, the main policy lesson of the paper.

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Appendix

A1 Additional Tables and Figures

Table A1: Comparison of main variables: EPH and ENMODO

Variable	EPH		ENMODO	
	Mean	SD	Mean	SD
Age (years)	35.01	22.34	34.01	21.37
HH Size	3.87	1.93	3.40	1.69
Rooms	3.01	1.11	2.64	1.03
Male (%)	0.49	0.50	0.49	0.50
Employed (% labor force)	0.94	0.24	0.90	0.30
Employed (% whole population)	0.46	0.50	0.43	0.50
Unemployed (% labour force)	0.06	0.24	0.10	0.30
Public employee (% total employment)	0.18	0.38	0.14	0.35
Primary education or less (%)	0.25	0.43	0.30	0.46
Secondary education (%)	0.20	0.40	0.36	0.48
Higher education (%)	0.14	0.35	0.13	0.34

Source: Author’s elaboration based on ENMODO and EPH. *Notes:* ENMODO contains 42,971 individual observations, which expand to approximately 16.5 million individuals. The EPH sample contains 17,014 individual observations, which expand to approximately 16.8 million individuals. All variables are reported at the individual level. Employed (labor force) reports the share of employed individuals among labor-force participants, while Employed (whole population) reports employment as a share of the total population. Unemployed refers to individuals actively seeking employment. Educational variables are mutually exclusive indicators representing the highest educational attainment or current attendance status.

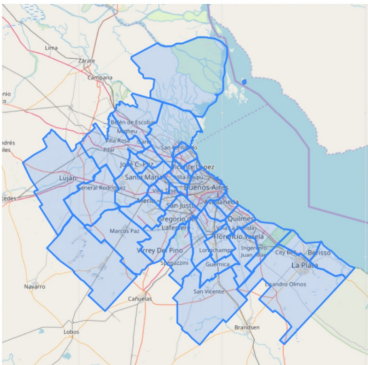
Table A2: Selected macroeconomic indicators for Argentina: 2018 and 2024

Indicator	2018	2024	Source
Economic Activity Index (EMAE, 2004=100)	145.8	144.2	INDEC
GDP per capita (constant USD)	13,058	12,774	WB
Unemployment rate (%)	9.2	8.15	INDEC
Population (millions)	44.495	47.164	INDEC
Labour force participation (%)	46.6	48.3	INDEC
Employment rate (%)	42.3	44.6	INDEC
Gini coefficient	0.430	0.442	INDEC
Real exchange rate (2015=100)	109.35	105.88	BCRA

Source: Own elaboration based on data from INDEC (Instituto Nacional de Estadística y Censos), WB (World Bank), and BCRA (Banco Central de la República Argentina).

Figure A1: Geographical coverage of AMBA

Área Metropolitana de Buenos Aires



Almirante Brown	Avellaneda	Berazategui
Berisso	Brandsen	CABA
Campana	Cañuelas	Ensenada
Escobar	Esteban Echeverría	Exaltación de la Cruz
Ezeiza	Florencio Varela	General Las Heras
General Rodríguez	General San Martín	Hurlingham
Ituzaingó	José C. Paz	La Matanza
Lanús	La Plata	Lomas de Zamora
Luján	Marcos Paz	Malvinas Argentinas
Moreno	Merlo	Morón
Pilar	Presidente Perón	Quilmes
San Fernando	San Isidro	San Miguel
San Vicente	Tigre	Tres de Febrero
Vicente López	Zárate	

Source: Authors' elaboration based on Ministry of Economy, Secretary of Transport.

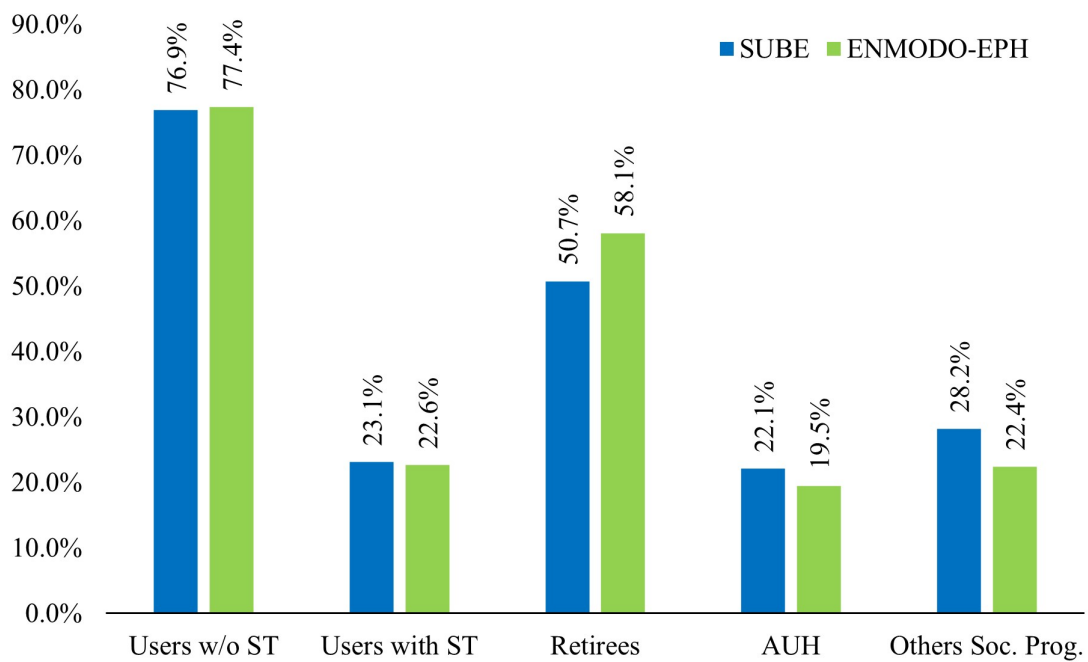
Figure A2: Fares for urban bus transport. April 2024. AMBA. In current pesos

Tarifas de colectivo			
Tramos	con SUBE registrada	Tarifa Social	con SUBE sin registrar
0-3 km	\$ 270	\$ 121,5	\$ 430
3-6 km	\$ 300,78	\$ 135,35	\$ 479,03
6-12 km	\$ 323,95	\$ 145,78	\$ 515,92
12-27 km	\$ 347,15	\$ 156,22	\$ 552,87
más de 27 km	\$ 370,18	\$ 166,58	\$589,54

 **Secretaría de Transporte**
Ministerio de Economía

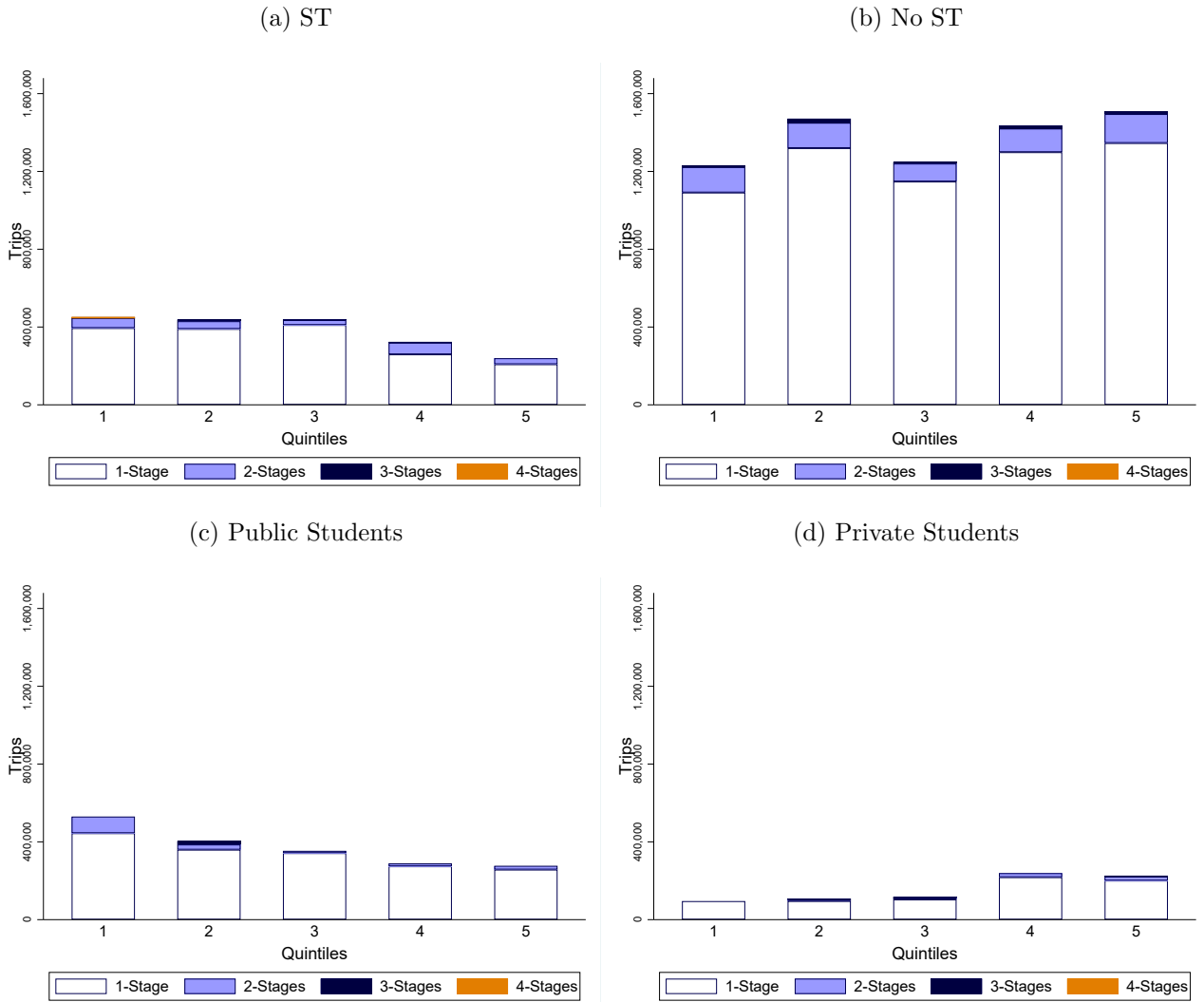
Source: Authors' elaboration based on Ministry of Economy.

Figure A3: Users by eligibility for ST: comparison between microdata and administrative records. Main groups. First semester of 2024



Source: Authors' elaboration based on EPH, ENMODO, and SUBE.

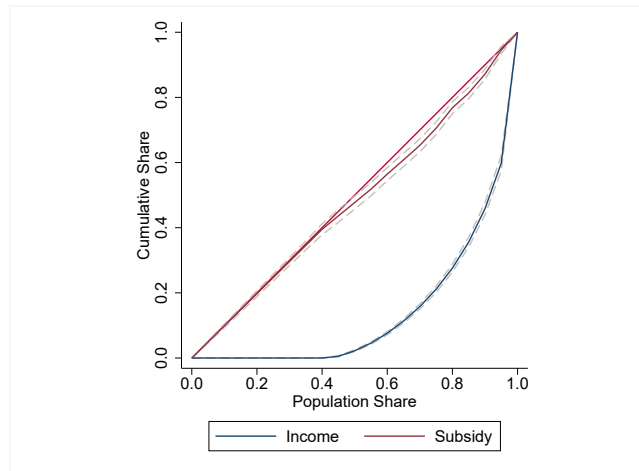
Figure A4: Trips in urban bus transport. AMBA. Main groups based on fare schemes. By per capita household income quintiles



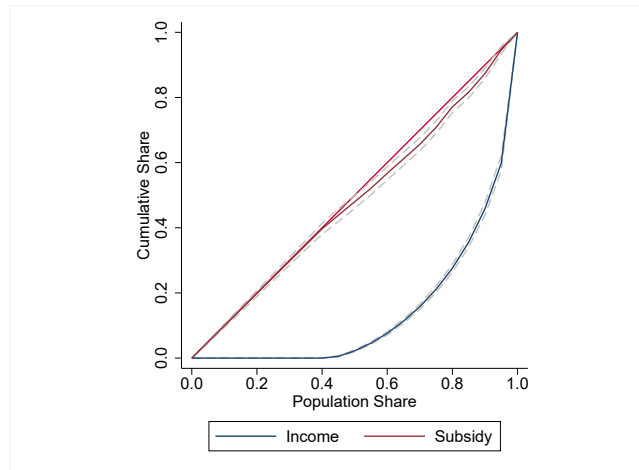
Source: own elaboration based on ENMODO 2018 and EPH 2024. Note: ST denotes Social Tariff. All values are weighted by the population growth factor.

Figure A5: Distributional impacts of potential fare increases in urban bus transport. AMBA.
Concentration and Lorenz curves

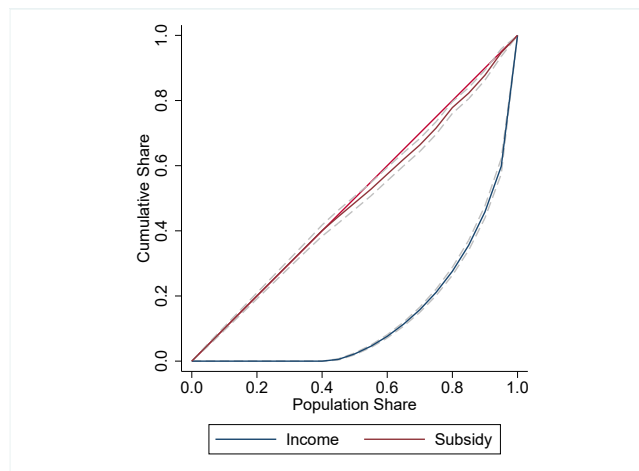
Panel A. 25 % fare increase



Panel B. 50 % fare increase



Panel C. 100 % fare increase



Source: own elaboration based on ENMODO 2018, EPH 2024, and Ministry of Economy. *Note:* All values are weighted by the population growth factor. Dashed lines represent 95% confidence intervals. The blue curve shows the Lorenz curve of income, while the red curve represents the concentration curve of the subsidy. The 45-degree line indicates perfect equality. If the concentration curve lies above (below) the Lorenz curve, the subsidy is progressive (regressive) in relative terms.