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Inequitable inefficiency: A case study of rail transit fare policies

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Abstract: Transit fare equity research overwhelmingly measures equity based on disparity in the fare paid for travel without consideration of the costs of service delivery. Research also ignores the cost-sharing nature of transit—as more riders consume it, the average cost per rider declines. Together, this leaves an incomplete understanding about who receives more subsidy. This study measures equity by analyzing spatial and temporal *cost recovery variability* of two rail systems, BART in the San Francisco Bay Area and MARTA in Atlanta. I scale origin-destination trip cost recoveries to stations and operating time periods and find that travel associated with outlying areas and off-peak times receive more subsidy. I further find that subsidy patterns are marginally progressive; they positively correlate with select disadvantaged socioeconomic groups. I offer ideas on why these findings appear divergent from past research.

Keywords: transit, equity, fare policy, transport subsidies, transportation finance

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1 Introduction

Since the 1950s, transportation finance policy in the United States has increasingly sought to treat travel as a public good such that travel-supportive infrastructure and services are to be primarily financed through collective taxes rather than user fees (e.g., Altshuler & Luberoff, 2004). As a result, travelers do not proportionally pay for the costs of their travel, if at all. This pertains regardless of mode. The *N*th driver on Boston's Big Dig (Interstate 93) or New York City's Major Deegan Expressway (Interstate 87) does not pay one-*N*th the costs of the maintenance of these roads, nor the marginal costs of additional capacity for and traffic impacts of their travel. Ditto for the *N*th transit rider in the Bay Area Rapid Transit District's (BART) Transbay Tube, the *N*th bicyclist using Utrecht Centraal's bicycle parking facility, and so forth. Thus, the provision of transportation is broadly inefficient since its costs are not fully paid by consumers. To the extent this inefficiency varies across portions of a network makes it *inequitably inefficient* and implies that *economic* subsidies of transport—the difference between the cost of providing transport and what travelers pay for the transport they consume—are not evenly distributed amongst travelers. These are distinct from *government* subsidies, which are taxpayer-funded monetary transfers that often fill the gap left from economic subsidies. I focus on measuring economic subsidies in this paper but discuss implications for how government subsidies are apportioned.

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Given that the provision and consumption of transportation are spatially and temporally variable, carefully evaluating the consumer incidence of transport subsidies—that is, how they are distributed across consumers—requires assessing how costs and user revenues covary across space and time. For example, highway and transit capacity, associated costs, and usage are generally highest in urban core areas and during weekday peak travel times. Do user fees correlate with this pattern such that the distribution of subsidies is equal across space, time, and travelers? If not, which group or groups of travelers are most subsidized?

Research on the incidence of transport subsidies is especially limited for public transit. This may be due to its dual policy objectives that inherently foster subsidization, including serving as a transportation lifeline for those who cannot or choose not to drive, and an alternative to driving that can reduce the negative externalities of driving (Elgar & Kennedy, 2005; Fielding, 1995, as cited in Giuliano, 2005; Meyer & Gomez-Ibanez, 1981). Indeed, luring travelers from driving to transit with capital and operating investments paid by others is a principal method of achieving the second objective. And internalizing the costs of transit service provision flies in the face of the first objective, as captive riders would not be able to afford much travel at all. As a result, whereas highway operations and maintenance (excluding capital expenses) nationwide experienced a revenue surplus from user fees (e.g., tolls, gas taxes, registration fees, etc.) in 2018 (United States Department of Transportation, Federal Highway Administration, 2019), transit operating costs were financed 33% through fares in the same year (United States Department of Transportation, Federal Transit Administration, 2019).

Yet, even if transit subsidies are accepted as an imperative to achieving transit's policy objectives, understanding who benefits most from transit subsidies can elucidate whether they are being used effectively. Are subsidies being allocated to places and times with high propensity for achieving travel mode shift or serving captive riders? Are subsidies being used in a cost-effective way such that the subsidy per benefit (e.g., rider, passenger-kilometer, car-to-transit mode shift, etc.) is minimized? Besides equity and effectiveness, are there side-effects of transit subsidies, such as induced development and travel, that warrant reconsideration of transit (and transportation) finance policies? For example, if achieving the goals of transit necessitates concentrating subsidies in cost-ineffective, low-density areas that are distant from urban activity centers, this suggests that transit subsidies reinforce sprawl patterns that are a common source of transportation and land use concern.

In this article, I contribute by using highly disaggregate cost, ridership, and fare data to examine spatial and temporal patterns of transit subsidies and whether this leads to socioeconomic disparities amongst transit riders. This is distinct from much transit fare equity literature that highlights disparities in what different travelers pay, or the amount of transit different communities receive, irrespective of the other (Mallett, 2025). I use the BART and Metropolitan Atlanta Regional Transit Authority (MARTA) rail systems as my case study and focus on fiscal year 2019 (FY19)—July 1, 2018, to June 30, 2019—as the study period to ensure no impact from the COVID-19 pandemic.

I hypothesize that travelers in outlying areas, travelers who travel longer distances (i.e., consume more kilometers of travel), and travelers who travel outside the weekday peak period each pay a lower share of their costs, but that the second hypothesis is attenuated with fare policies that are distance based. In other words, I hypothesize that non-peak-period travel, long-distance travel, and travel to/from suburban and exurban areas are disproportionately subsidized relative to peak-period travel, short-distance travel, and trips within urban core areas; distance-based fare policies, however, can reduce this effect for long-distance travel.

In the following section, I discuss research to date on the incidence of transit subsidies and fare equity, noting key distinctions in studies that do and do not account for costs. I then contextualize BART and MARTA and explain the basis for selecting them as case studies. While some general data about the agencies and travel patterns they serve are discussed here, I reserve the data used in my analysis for the sections that succeed, namely, Data and Methods and Descriptive Statistics. Finally, I summarize results and discuss their implications for planning and policy. Because I perform two parallel analyses—spatial and temporal—some sections are subdivided accordingly. Throughout the article, I interchangeably use "cost recovery" and "subsidy," depending on the context, such as whether I am emphasizing an operator's overall efficiency or the subsidy inequities amongst riders. The total cost of serving a trip, less the subsidy a rider receives, is the cost recovery for that trip; the total cost, less the cost recovery equals the subsidy.

2 Transit pricing and expenditure research

Research on the equity and efficiency of how United States transit is priced and delivered has evolved over the past half century. Throughout the 1970s and 1980s, studies evaluated equity and efficiency based on cost recovery or fare-per-mile disparities amongst geographic areas or times of travel. However, the studies suffer from using aggregate units of analysis that shadow disparities amongst riders. For example, by aggregating service output and fare revenue to "urban" and "suburban" categories of the municipalities served (e.g., Cervero, 1981; Hodge, 1988; Iseki, 2016), an implicit assumption is made that all trips that are urban or suburban are equally subsidized. Since the 2000s, as transportation equity scholarship has grown outcomes-based, transit pricing and expenditure equity research has focused primarily on whether fare structures charge travelers either proportional to the miles they travel or proportional to their income level, and, if not, what the socioeconomic implications are (Mallett, 2025). This leaves a gap in understanding another perspective of equity, which is whether there is parity in the share of costs travelers pay for the transportation they consume—in other words, how subsidies are distributed amongst travelers.

Government transit subsidies are typically classified as supply side or demand side, depending on whether they pay for the supply of transit or discount the price of transit for consumers, respectively. Much research about the impacts of transit subsidies is through this lens. In their literature review, Serebrisky et al. (2009) found that most supply-side subsidy programs are socioeconomically neutral or regressive, while few demand-side subsidies are effective in achieving either of the previously discussed policy objectives of transit. Other research has shown that supply-side subsidies lead to increased pay and benefits for unionized transit workers rather increased levels of transit service for travelers (Jones, 1985; Morales Sarriera & Salvucci, 2016; Pickrell, 1985; Sarriera et al., 2018; Wachs, 1989). However, focusing on whether central government subsidies are paid to suppliers or consumers obscures variability in where and to whom subsidies ultimately flow. While a transit agency may be 60% subsidized by central government funds, this says little about how the subsidies are distributed across municipalities, neighborhoods, and riders of the network. Perhaps half of the network's service is self-sufficient, and the subsidies are paying for the operation of select underperforming segments of the network. Who are the beneficiaries and payors of this subsidy pattern, and is this equitable? Similarly, demand-side subsidies only account for the difference between what a rider pays and the fare normally charged by a transit agency, which says little about the trip-level subsidy—the difference between what the rider pays and the cost of their trip.

Another dimension of transit pricing and expenditure research pertains to the user equity of transit fare structures, which is the primary literature with which I engage. This literature has converged to measure equity based on what travelers pay without regard to the cost of services rendered—what I call the "pricing axis" (Mallett, 2025). Studies that considered costs were most popular in the 1980s as transit agencies migrated from using time- and distance-variant fare structures to flat-rate fare structures. Researchers and policymakers sought to understand the equity and efficiency implications of this transition. To account for cost variability, studies of the era employed cost allocation models in which input-output relationships are used to allocate categories of costs to service outputs (i.e., occasions of costs). For example, power supply costs may be allocated proportionally to vehicle-kilometers and labor costs to vehicle-hours. Once all costs are allocated to different dimensions of a network, such as time periods (i.e., operating times that a transit provider scales service levels to) or service routes, the result can explain disparities in expenditure patterns. Studies of this time (hereafter, "earlier research") included those that considered only disparities in expenditure (e.g., Cherwony & Mundle, 1978, 1980; Taylor et al., 2000) and those that considered disparities of pricing relative to expenditure, or subsidies (e.g., Cervero, 1981; Hodge, 1988; Parody et al., 1990; Reilly, 1977). More recent studies (hereafter, "newer research") have almost exclusively considered pricing only (e.g., Bandegani & Akbarzadeh, 2016; Farber et al., 2014; Nuworsoo et al., 2009)

With few exceptions, earlier research finds that it is more costly to serve peak-period travel than off-peak-period travel in both net and gross terms—meaning, respectively, whether fares are or are not accounted for in the analysis. Earlier research also finds that urban *riders* subsidize suburban *riders*, but the collective of suburban *riders and taxpayers* subsidizes the collective of urban *riders and taxpayers*. On the latter point, Hodge (1988) found that urban riders in Seattle, WA partly cross-subsidize suburban riders when only farebox recovery is considered, but that when the tax base is accounted for, the flow of subsidies is reversed. The policy implication of this is that urban riders pay a higher share of their costs (though not 100%), so are less subsidized, but that transit's reliance on taxpayer subsidies politically obligates operators to provide disproportionate levels of service in suburban and exurban areas relative to the ridership and fare revenues generated therefrom. Cervero (1981), also documented in Cervero and Wachs (1982), studied three California transit agencies and found that peak-period and suburban services are more costly than off-peak and urban services. He also found that suburban trips are longer and generate less revenue per passenger-mile under a flat-rate fare structure; and that low-income and minority riders tend to take trips that are shorter, urban, and off-peak. He concludes that flat-rate fares are cost-recovery inequitable and regressive.

Of the earlier research, only Reilly (1977) found that the peak period is less subsidized than off-peak periods. A deciding factor of Reilly's divergent finding appears to be his exclusion of fixed and semi-fixed asset costs. In contrast, Cervero (1981) and Parody et al. (1990) allocate asset costs 85% to the peak period and 15% to the off-peak period in evaluating cost recovery variability, Taylor et al. (2000) use a marginal cost allocation method (Savage, 1989) based on the share of transit vehicles in use during different time periods, and all studies found the peak period to be the most subsidized. Key limitations of earlier research include the use of, at best, weakly disaggregate data—such as allocating costs and fare revenues to just two time periods (e.g., Cervero, 1981; Parody et al., 1990; Reilly, 1977), bus yard "cost centers" (e.g., Cervero, 1981), or "urban" and "suburban" labeled geographies (e.g., Hodge, 1988) to evaluate temporal and spatial variability of costs and subsidies. In addition, earlier research almost exclusively focuses on bus transit. I elaborate more on the findings of these studies and the development of cost allocation methods in Mallett (2025).

Since the early research era, data granularity has greatly improved, which can allow for much more informative findings about how costs, farebox recovery, and subsidies vary by time and location. Yet, newer research has tended to ignore costs. Bandegani and Akbarzadeh (2016) merely test if distance-based fares are more equitable at charging riders proportional to the amount of travel they consume. The answer is self-evident. Farber et al. (2014) used highly granular geographic data to test whether the impact of the Utah Transit Authority converting from flat to distance-based fares would vary by socioeconomic groups of riders. They found that the socioeconomic impacts cannot be generalized because each socioeconomic group consumes different amounts of travel in different areas of the state. And Nuwusoo et al. (2009) analyzed the equity impacts of various possible changes to the Alameda–Contra Costa Transit District's (AC Transit) fare structure, most notably the implications of charging per trip segment or per trip inclusive of transfers. They found the former disproportionately burdens marginalized communities because they are subject to making more transfers to complete their trips. Apart from my cost and cost-effectiveness study that is a precursor to this research (Mallett, 2022), I found just two newer studies that consider costs. However, they rely on past study findings to inform their analysis (Brown, 2018) or continue to use highly aggregate time periods (Brown, 2018) and geographies (Iseki, 2016). Brown (2018) uses the 45% peak-to-base net cost ratio from Parody et al. (1990) based on 1983 national aggregate data and 2012 California Household Travel Survey data to conclude that the flat-rate transit fare structure in Los Angeles is regressive and would be more equitable under a time- and distance-variant structure. Iseki (2016) conducted a similar study as Hodge (1988) focused on Toledo, OH, and found similar results. Other newer studies are international and also tend to assess fare equity based on pricing alone, though some highlight that distance-based fares are regressive in some countries due to socioeconomic sorting patterns (e.g., Rubensson et al., 2020; Zhao & Zhang, 2019).

Finally, a common shortcoming of transit pricing and expenditure equity research is that it does not consider production economies, network economies, or demand response to fare adjustments. While it may be "inequitable" that some riders pay more than others or that some neighborhoods receive a disproportionate share of vehicle-kilometers of service, correcting these inequities through fare changes or reallocating resources may increase total or average operating costs or alter ridership only to create new patterns of inequity. Similarly, dividing a transit system into parts and honing in on their differences overlooks the network effect; many riders across multiple OD pairs pass through parts of a network where costs per rider are low, even as costs per rider in outlying areas are high. The analysis that follows is also subject to these criticisms. However, transport economic models that can measure the incidence of user costs and benefits while controlling for aggregate economies remain underdeveloped. As a result, cost allocation models continue to be used to understand distributive variations (Basso et al., 2011; Mallett, 2024).

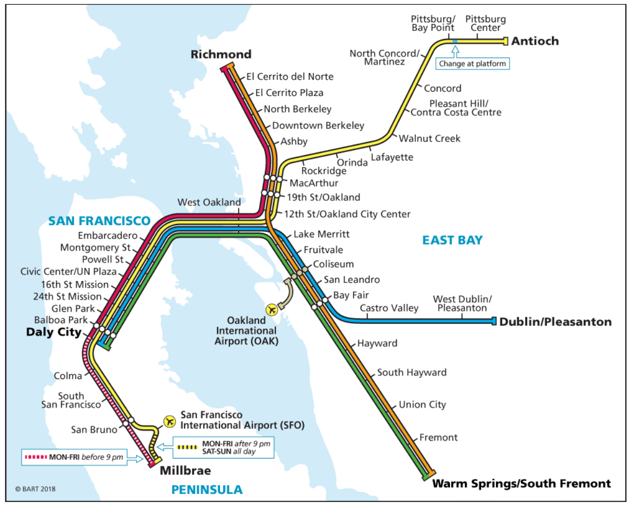
In sum, past literature suggests that, when asset costs are accounted for, the peak period is subsidized more than the off-peak period, but that the pattern is reversed when these costs are not accounted for; flat-rate fare structures are socioeconomically regressive because they allow persons who consume longer and more suburban trips—who tend to be white and wealthy—to pay both less per mile and less of their trip costs; and urban areas pay a higher share of travel costs through fares than suburban areas, but a lower share on net when tax source revenues are accounted. Among missing elements in the literature are more thorough analyses of transit modes other than bus transit, as well as the use of available granular data to evaluate temporal and spatial variability of cost recovery patterns more precisely. For example, transit operators' time periods often are more nuanced than merely peak and base, and spatial variability is more varied than geopolitical boundaries. Most significantly, extensive spatial fare equity research measures price per kilometer disparity, which overlooks the cost-sharing nature of transit and assumes uniform per-kilometer costs of serving a trip. Specifically, as more travelers use a transit service, the cost per traveler decreases, and this can vary by location—an aspect not accounted for using price-per-kilometer disparity metrics. Some game theory literature on how transit riders may change travel patterns in a cost-sharing scheme (Rosenthal, 2017), as well as research on private-sector "collaborative transportation" concepts (e.g., Frisk et al., 2010; Guajardo & Rönnqvist, 2016), exists, but no research on transit cost recovery and fare equity accounts for this.

3 About BART and MARTA

BART and MARTA are 1970s-era regional rapid rail transit systems. They are distinct from metro rail or subway services, like the New York City Subway and the Massachusetts Bay Transit Authority's T system, as well as traditional commuter rail services, like Caltrain on the San Francisco Bay Peninsula and Metra in Chicago. Metro rail systems are characterized by being high-frequency, frequent-stop, fully grade separated, and catering to a principally urban travel base. By contrast, commuter rail services cater to long-haul suburban and exurban commuters, usually have more spacing between stops, extensively scale their services to cater to peak-period travel, are not subject to grade separation, and generally converge all routes around a downtown "union" station. Regional rapid rail transit systems are effectively a blend of these models. They bring the benefits of automated train control and rapid electric propulsion of metro rail services to longer-haul *regional* travel. With automation, trains can run at routine speeds and headways, and, with electrically propelled high speeds and acceleration, the time expense of stopping is significantly less than for commuter rail services that often must employ skip-stop service to overcome the cost.

I selected BART and MARTA as case studies because of their comparable operating characteristics, coupled with their having distinct fare structures—distance based and flat rate, respectively. Thus, going into the research, I theorized that any difference in findings between the two agencies would be explained by fare structure. Furthermore, the two agencies have highly granular trip and operating data, making them viable candidates for the research. For example, the entry, exit, and fare of every trip made, as well as the run time and railcar length of every scheduled train run, are recorded. The Washington Metropolitan Area Transit Authority, which is the only other comparable regional rapid rail transit system in the United States, was to be included and would have added an additional fare type for comparison, time-variant fares. However, agency staff did not provide all data needed for inclusion. Figure 1 shows the system maps in use by BART and MARTA during most of FY19.

During FY19, MARTA's flat-rate fare was $2.50 per trip. However, it offered various discounts, including through transfer agreements with other transit operators, cooperative arrangements with area employers, multi-day passes, and more. At BART, base fares are distance based but follow a stepwise function. Riders pay a minimum fare for the first six miles (approximately 9.6 kilometers) of travel. Beyond six miles, riders pay for the first six miles plus a rate per mile up to 14 miles (approximately 22.5 kilometers); beyond 14 miles, riders pay for the first 14 miles plus a lower cost per mile greater than 14 miles. Accordingly, although riders pay more for every additional mile traveled beyond six, longer-distance travel is discounted on a per-mile basis. There are also various fees, including a fee for use of the Transbay Tube, for travel to or from San Mateo County stations, and for travel to or from San Francisco and Oakland international airports; as well as various discount programs, including for senior and disabled riders, youth, and high-value discount tickets. I account for these many fees and discounts in OD pair cost recoveries by using the weighted average fare paid for the OD trip.



A: BART (effective July 1, 2018, to February 10, 2019)

B: MARTA (Effective FY19)

Figure 1. Agency system maps

Table 1 provides agency profile information of the BART and MARTA rail networks effective during FY19. Unless otherwise noted, this comes from the cost allocation portion of this research (Mallett, 2022). As in the cost allocation research (Mallett, 2022), while I include all BART stations in Table 1 and the following analysis, only mainline portions of BART track are included for consistency (i.e., I exclude BART's diesel-multiple unit eBART service and cable-powered Oakland Airport Connector service). During FY19, the MARTA system had 38 stations, resulting in 703 two-way OD pairs compared to 48 stations and 1,128 two-way OD pairs for BART. Notably, although

BART has a network about 2.3 times the size of MARTA's, it generated 3.5 times as many vehicle revenue-km and 3.9 times as many trip-km, but only 1.9 times as many trips.

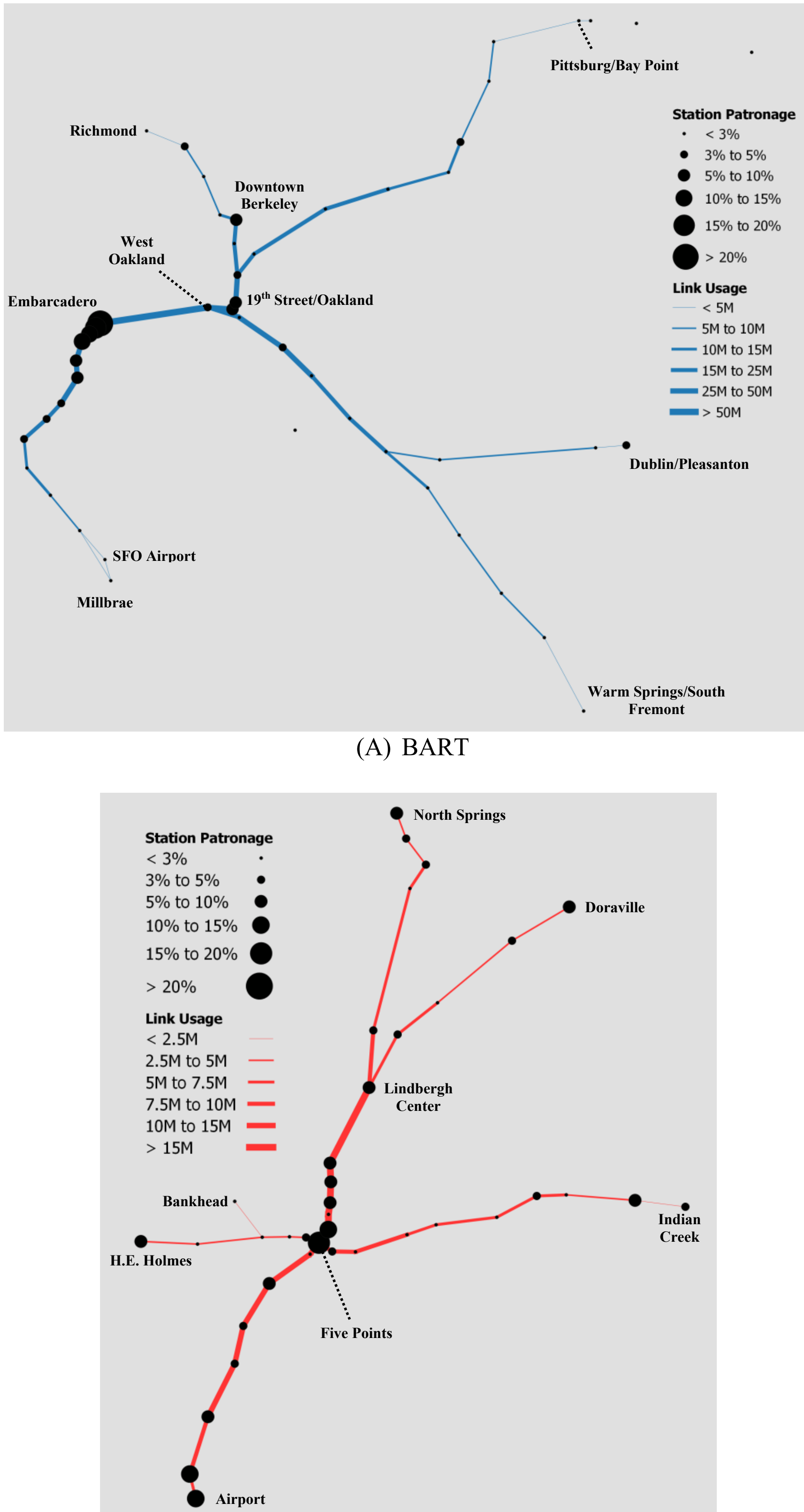
Table 1. Agency profiles

	BART	MARTA
Mainline kilometers (miles)	176 km (109.4 miles)	77.2 km (48 miles)
Stations	48 stations	38 stations
Fare structure	Distance-based	Flat rate
Net fare revenue	$448,688,735	$58,576,496
Gross costs	$847,799,127	$237,992,718
Farebox recovery ratio	52.9%	24.6%
Vehicle revenue-kilometers* (revenue-miles)	125.5M vehicle-km (78M vehicle-miles)	37M vehicle-km (23M vehicle-miles)
Annual trips	125M trips	65M trips
Annual passenger-kilometers (passenger-miles)	2.826B passenger-km (1.756B passenger-miles	724.2M passenger-km (450M passenger-miles)

**As reported in 2019 Agency Profiles of National Transit Database*

The spatial pattern of travel in the two systems is also distinct, which can influence how trip length and the extent to which trips are oriented around the urban core (i.e., the urban-suburban "balance" of a trip) shape spatial cost recovery patterns. BART's OD ridership patterns revolve around a monocentric center, downtown San Francisco, whereas MARTA's OD ridership patterns are polycentric if not broadly dispersed. About two-thirds of all trips taken in the BART system begin or end at its four busiest stations in downtown San Francisco. Further, every other BART station's ridership has its highest destination relationship with one of the four busiest stations, ranging from 10% to 30%, with an average of 19%. And when the busiest stations are analyzed as a group, between 29% and 73% (with a 50% average) of trips from every other BART station is destined for downtown San Francisco. By comparison, just more than half of all trips taken on MARTA begin or end at its four busiest stations, these stations are associated with two epicenters of ridership, downtown Atlanta and the airport, and just 79% of other stations have their strongest destination relationship with one of these. Just 51% of trips begin or end at a downtown Atlanta station—North Avenue, Civic Center, Peachtree Center, Five Points, Garnett, Georgia State, Dome/CNN Center, and Vine City stations. In both systems, the four busiest stations are the only stations with a double-digit share of passenger patronage.

While station patronage is relatively monocentric for BART and dispersed for MARTA, the ridership along links is centrally concentrated in both networks. This is reflected in Figure 2 and makes sense, as trip paths can be centrally concentrated along links of a network even if origins and destination are not. This is especially likely if the network has a defined central node that many OD trips must pass through, as is the case for MARTA. I investigate these observations more thoroughly in the Results section.



(A) BART

(B) MARTA

Figure 2. Spatial pattern of station patronage and link usage

4 Data and methods

My objective in this research is to evaluate whether transit rider subsidy levels significantly vary across locations and times of travel and examine how fare structures influence these patterns and their socioeconomic implications. Additionally, I test whether spatial subsidy patterns are more strongly explained by trip length or how spatially removed trips are from the urban core of the network. This analysis tests the common assumption in fare policy research that trip costs correspond with trip length (e.g., Brown, 2018; Cervero, 1981). Methodologically, I allocate fares and costs to locations and times of travel, calculate cost recovery levels, and use ordinary least square (OLS) regressions to evaluate spatial patterns at the OD trip level. I assess temporal patterns and spatial patterns at the station and link levels using correlation analysis. I elaborate on data and methods in the following subsections.

4.1 Data

To evaluate spatial and temporal subsidy patterns, I build on the cost allocation study (Mallett, 2022), where I document the long-run (i.e., recurring) costs of serving different locations and times of travel within the BART and MARTA networks. Thus, in Mallett (2022), I allocated personnel costs and annualized semi-fixed asset costs (e.g., railcars and heavy maintenance equipment), but excluded sunk costs (e.g., construction and land purchasing). Briefly, I found that costs decrease, but costs per rider increase, with distance from the core of the BART system. For MARTA, no spatial pattern emerged. Temporally, I found that BART and MARTA scale service levels to eight and five distinct time periods, respectively; the weekday peak period had the lowest cost per rider but the highest total costs for BART; and MARTA's weekday peak costs were only slightly higher than its weekday base period but had the lowest cost per rider.

In the present study, I append fare receipt data and socioeconomic data to examine subsidy patterns and their impacts. All ridership and fare data—recording of the origin station, destination station, time of entry, and fare payment for all trips made in FY19—come from BART and MARTA. To assess socioeconomic implications, I use rider survey data from BART's 2015 Station Profile Study and the Atlanta Regional Commission's (ARC) 2019 Transit On-Board Survey. BART's data are pre-weighted to 2015 station trip volumes, whereas ARC's data consist of original survey entries with origin and destination station details. To make ARC's survey sample representative of actual station usage, I weight trip counts in the survey to match FY19 ridership data.

For analytical consistency with Mallett (2022), I exclude trips that solely use non-mainline BART tracks, resulting in 1,124 two-way OD pairs rather than 1,128. Additionally, I do not differentiate trips by directionality; a trip between two stations is analyzed together with its reverse trip.

4.2 Methods

Measuring cost recovery variability requires analyzing how costs and fare receipts covary across time and space. Below, I detail the spatial methods in greater detail, as they are more complex.

To analyze temporal cost recovery variability, I compute the ratio of total fare revenues to total costs by time period (Equation 1). I also conduct pairwise correlations to assess interactions among cost recoveries, passenger-kilometers, trip counts, and spatial variables across time periods (discussed below). Since ARC and BART did not survey weekend riders, and the number of time periods is limited, there is insufficient data to evaluate the socioeconomic implications of temporal subsidies.

$$percentpaid_t = \frac{fares_t}{cost_t} \tag{1}$$

where
percentpaid$_t$ is the cost recovery during time period, *t*
fares$_t$ is the amount of fare revenue generated in time period, *t*, and
cost$_t$ is the total costs allocated to serving time period *t* (see Mallett, 2022)

Analyzing spatial cost recovery variability is more complex because OD trip subsidy disparities do not directly translate into geographic subsidy distributions across stations and links. Multiple travelers may begin or end their trips at the same station or share common links while making different OD trips. Consequently, OD-level cost recoveries alone do not fully explain how subsidies spatially concentrate—for example, whether riders of a particular station receive disproportionately high subsidies. Additionally, unlike time periods, which are one-dimensional, there is no straightforward way to divvy up fares into link and station parts (two dimensions). Given these considerations, I do not devise link and station cost recoveries, per se. Instead, I calculate OD trip cost recoveries, then scale these values to stations and links by taking averages over trips that use each station or pass through each link. This allows me to approximate the spatial incidence of subsidies across the network and also informs the socioeconomic analysis.

To estimate OD trip costs, I sum the costs per rider—derived from Mallett (2022)—of the origin station, destination station, and each link used to complete the trip (Equation 2). For BART trips that partially use non-mainline tracks, I calculate link costs using only the mainline links of the network. The OD cost recovery rate then is the ratio of the average fare paid for an OD trip to the OD trip cost (Equation 3).

$$cost_{od} = costppx_o + costppx_d + \sum_{l=1}^{n} costppx_l \tag{2}$$

$$percentpaid_{od} = \frac{fare_{od}}{cost_{od}} \tag{3}$$

where
cost$_{od}$ is the cost of serving a particular OD trip, *od*,
costppx$_o$ is the cost per passenger of origin station, *o* (see Mallett, 2022),
costppx$_d$ is the cost per passenger of destination station, *d* (see Mallett, 2022),
costppx$_l$ is the cost per passenger of link, *l* (see Mallett, 2022),
percentpaid$_{od}$ is the cost recovery of a particular OD trip, *od*, and
fare$_{od}$ is the average fare paid for consuming a particular OD trip, *od*

To test how much trip subsidies are explained by trip length, while controlling for their orientation around the urban core, I run OLS regressions. Specifically, I regress the log of OD cost recovery (*percentpaid$_{od}$*) on the log of trip length (*triplength*) and the log of a measure of how centered OD trips are around a defined core station (*decentralization*), as expressed in Equation 4. *Decentralization* more explicitly measures the average straight-line distance the origin and destination stations are from the defined core station. For example, if the origin station is 50 miles from the core station and the destination station is 20 miles from it, the *decentralization* value for this OD pair would be 35 miles. Hereafter, I refer to this measure as the "decentralization score." For BART, I define West Oakland as the core station; for MARTA, Five Points.

$$\ln(percentpaid_{od}) = \beta_0 + \beta_1 \ln(triplength) + \beta_2 \ln(decentralization) \tag{4}$$

where
$percentpaid_{od}$ is the cost recovery of a particular OD trip, *od* (see Equation 3),
triplength is the trip length, in track-kilometers, of a particular OD trip, and
decentralization is the average straight-line distance, for a particular OD trip, that the origin and destination stations are from a defined core station.

In essence, *decentralization* proxies for an OD pair's urban monocentricity. OD pairs with both endpoints near the core have a low decentralization score; those with both endpoints far from the core, high decentralization scores; those with one endpoint near the core and one far (e.g., suburban commutes), moderate decentralization scores. Importantly, *decentralization* does not necessarily correlate with trip length; a high decentralization score could correspond to a long trip between two distance suburbs that passes through the core, as well as a short intra-suburban trip. In addition, I use straight-line distance instead of track mileage because it more accurately captures monocentricity, which has the added benefit of further mitigating potential collinearity with trip length.

The model in Equation 4 measures how well two elements of costs are recovered through fares: a distance element and a geography element. The distance element reflects that, generally, the more travel one consumes, the more it costs to serve them. This is captured in the *triplength* variable. The geography element refers to how costs can spatially vary, which I hypothesize is influenced by how much a trip revolves around an urban core. This element of costs is captured in the *decentralization* variable.

To understand the geographic and socioeconomic incidence of subsidies, I develop cost recovery profiles of stations and links. These profiles reflect the weighted average cost recovery of OD trips associated with a given station or link. I define these calculations in Equations 5 and 6. Referring to Figure 1(a), a trip from MacArthur to Fruitvale and a trip from Dublin/Pleasanton to Montgomery Street will both contribute to the weighted average cost recovery profile of the Lake Merritt–Fruitvale link, but only the former trip will count toward Fruitvale Station's cost recovery profile.

$$percentpaid_s = \frac{\sum_{s=o,d}(trips_{od} * percentpaid_{od})}{trips_s} \tag{5}$$

$$percentpaid_l = \frac{\sum(trips_{od} * percentpaid_{od}) \in l}{trips_l} \tag{6}$$

where
$percentpaid_s$ is the cost recovery profile of a particular station, *s*,
$trips_{od}$ is the total number of times that a particular OD trip, *od*, was consumed,
$percentpaid_{od}$ is the cost recovery of a particular OD trip, *od* (see Equation 3)
$trips_s$ is the total number of trips to and from a particular station, *s*,
$percentpaid_l$ is the cost recovery profile of a particular link, *l*,
$trips_l$ is the total number of trips that traverse a particular link, *l*,

I use these cost recovery profiles to evaluate the spatial incidence of subsidies and their broader implications in two ways. First, I assess whether station and link cost recovery profiles correlate with their distance from the core station and riders' travel patterns, including average trip lengths and decentralization scores. This analysis is conducted both graphically and through one-to-one regressions. Unlike prior studies (Cervero, 1981; Hodge, 1988; Iseki, 2016), which label areas using an "urban"/"suburban" binary, I treat urban-suburban as a continuum. Second, I run pairwise correlations to examine relationships among cost recovery profiles, various travel metrics (trip counts, average trip length, decentralization scores, etc.), and the share of racial and income groups' make-up of a station's ridership. I conduct similar analysis for time periods, excluding socioeconomic variables due to data limitations, and present these findings using correlation matrices. These analyses help reveal how different subsidy levels, consumption patterns, and (for stations) socioeconomics relate across stations and time periods. While regression analysis using OD data would be ideal, it is infeasible because socioeconomic data are unavailable at this granularity, and with only 38 MARTA stations and 48 BART stations, sample sizes are too small for multivariate regression.

5 Descriptive statistics

In this section, I present descriptive data on the distribution of costs, fares, ridership, and cost recovery across OD pairs and their aggregation to stations, links, and times of travel. I review these data both unweighted and weighted to OD trip count to illustrate that the distribution of these metrics based on actual travel consumption is markedly different from what would occur if travel were evenly dispersed in the two networks. Throughout, I contrast BART's and MARTA's descriptive data to underscore differences in travel patterns and system design that may influence analytical results.

5.1 OD cost recovery

Table 2 shows descriptive statistics of variables in the OD cost recovery analysis—cost recovery ($percentpaid_{od}$), the average distance the origin and destination stations are from the core station (*decentralization*), the OD trip length in track-kilometers (*triplength*), and the count of times the OD trip was consumed in FY19 (*trips*). I show both unweighted (UW) distributions and distributions weighted (W) to OD trip count. The unweighted statistics reflect the overall distribution of cost recovery across the network, incorporating general ridership patterns but without adjusting for how specific OD pairs are used. While unweighted statistics consider ridership at the network level (since this is used to estimate trip costs), they do not account for the frequency with which individual OD pairs are traveled, treating each OD pair equally. In contrast, the weighted statistics scale these values based on the actual frequency of trips between each OD pair, providing a more accurate picture of variability in trip-level cost recovery. I use unweighted values for the regression analysis, as these explain the *occasions* of subsidies, but I show both unweighted and weighted statistics to highlight how patterns at the OD pair level differ from those in aggregate trip consumption—insights that are critical for understanding the *incidence* of subsidies, which I assess in the station and link analyses.

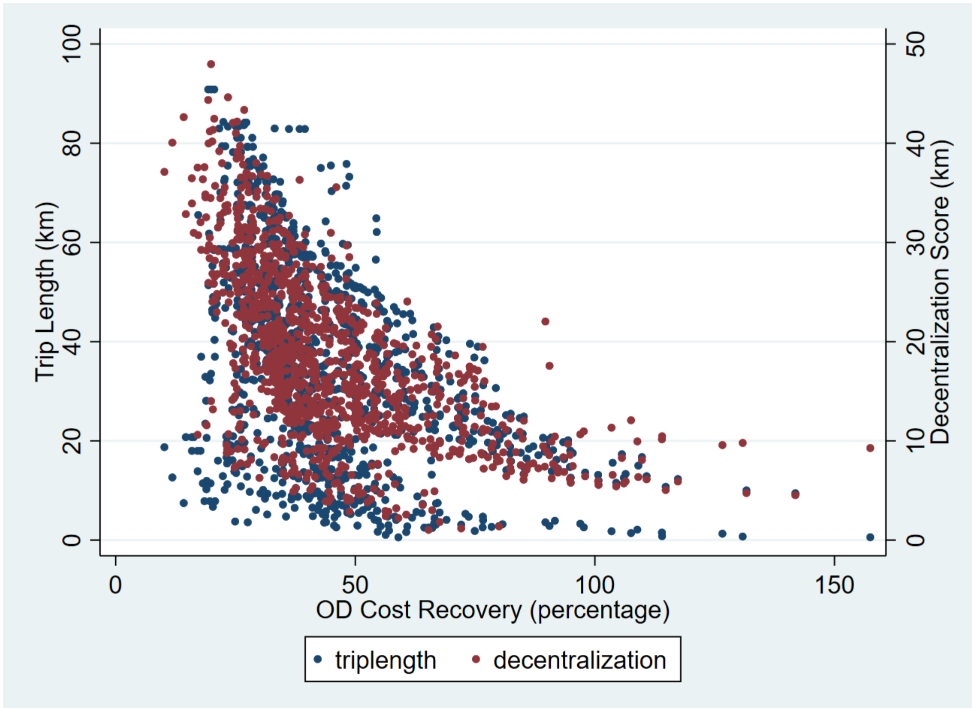
Table 2. Descriptive statistics of OD pairs

Agency	Variable	Minimum	Mean		Median		Standard Deviation		Maximum
			UW	W	UW	W	UW	W	
BART	*percentpaid$_{od}$*	10.16%	44.24%	63.31%	39.35%	57.11%	19.24%	25.6%	157.46%
	decentralization (miles)	1.03 (0.64)	18.73 (11.64)	14.1 (8.76)	17.75 (11.03)	12.91 (8.02)	8.53 (5.3)	6.69 (4.16)	47.97 (29.81)
N (two-way OD pairs) = 1,124	*triplength* (miles)	0.56 (0.35)	35.12 (21.82)	24.11 (14.98)	33.75 (20.97)	20.33 (12.63)	20.12 (12.5)	16.19 (10.06)	90.83 (56.44)
	trips	354	104,514.5	—	31,702.5	—	184,272.8	—	1,372,116
MARTA	*percentpaid$_{od}$*	10.2%	30.10%	36.05%	27%	31.44%	13.38%	17.51%	105.25%
	decentralization (miles)	0.29 (0.18)	8.03 (4.99)	8.14 (5.06)	7.39 (4.78)	7.77 (4.83)	4.43 (2.75)	4.31 (2.68)	20.73 (12.88)
N (two-way OD pairs) = 703	*triplength* (miles)	0.61 (0.38)	15.48 (9.62)	14.69 (9.13)	14.56 (9.05)	13.6 (8.45)	9.59 (5.96)	9.75 (6.06)	42.47 (26.39)
	trips	725	58,682.16	—	30,181	—	77,612.73	—	687,245

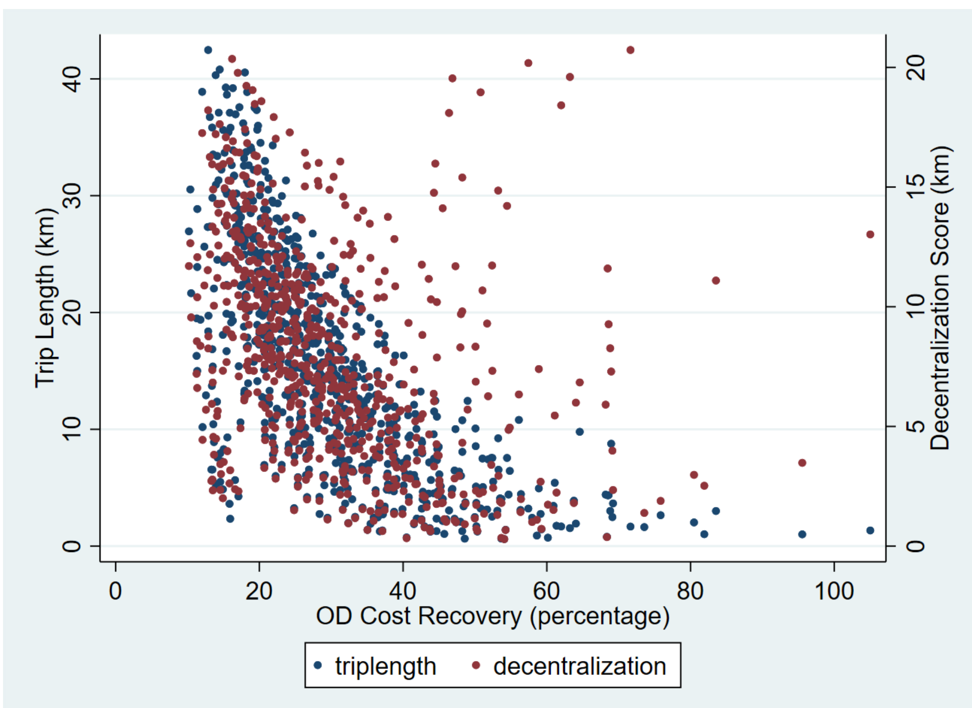
The difference between the two networks in how unweighted (i.e., OD pairs, irrespective of trip count) and weighted (i.e., total OD trips) statistics vary is noteworthy. For BART, weighted metrics differ significantly from unweighted ones, indicating that trip consumption is unevenly distributed across the network. Specifically, the average cost recovery of trips consumed (weighted) is 1.4 times *higher*, average trip length 31% *shorter*, and travel is 25% *more* core-oriented than if trips were evenly spread across all OD pairs (unweighted). By comparison, MARTA's trip consumption patterns closely resemble the unweighted distribution, suggesting more uniform trip distribution. Additionally, while BART trips are longer and more "suburbanized" (decentralization score) in absolute terms, MARTA trips are longer and extend farther into suburban areas relative to the network's total span. On BART, the average consumed trip has origin and destination stations with an average straight-line distance from the core station of 14.1 kilometers (8.8 miles), or 29% of the maximum possible. The same metric for MARTA is 8.1 kilometers (5.0 miles), or 39% of the maximum possible. Similarly, the average trip length of consumed trips on BART is 24.1 kilometers (15 miles), or 27% of the longest possible trip, while MARTA's is 14.6 kilometers (9.1 miles), or 35% of its maximum extent.

One last point on Table 3. It may seem counterintuitive that the systemwide cost recoveries of 53% for BART and 25% for MARTA (from Table 1) do not match the unweighted or weighted mean cost recoveries in Tables 3 and 4. This is because OD pair and trip-level cost recoveries are determined after dividing a system into its component parts, with costs and fare revenues assigned to the trips that use them. In contrast, systemwide cost recovery is calculated by dividing total fare revenue by total costs. As a result, OD pair and trip cost recoveries do not necessarily center around the systemwide value since they are derived from different cost and fare distributions. This distinction highlights a key objective of this research: understanding cost recovery at a granular level reveals patterns that are not apparent from systemwide averages alone.

Figure 3 graphically shows the two independent variables' relationship with the dependent variable. Consistent with my general hypotheses, both trip length and the average distance of the entry and exit stations from the urban core have an increasingly negative relationship with cost recovery. However, particularly for MARTA, there are outliers for the latter independent variable. As I more thoroughly assess in the results section, the positive outliers are associated with travel around an outer job center of the region, where many short trips share links and stations with long-distance trips, thereby reducing costs per rider and increasing cost recoveries for these trips.



(A) BART



(B) MARTA

Figure 3. Cost recovery vs. trip length and average OD station distance from core

5.2 Station- and link-level analysis

Tables 3 and 4 show the descriptive statistics for the station-level analysis for BART and MARTA, respectively, while Table 5 presents the same for the link-level analysis. As previously mentioned, these statistics are weighted averages of the OD data, based on OD trip count and conditional on a station being an origin or destination, or a link being traversed in completing an OD trip. Income and race variables in Tables 3 and 4 represent the percent share of riders at each station in different income bands (noted in thousands) and racial groups—American Indian (*rai*), Asian or Pacific Islander (*rapi*), Black or African American (*rblack*), Hispanic (*rhisp*), White (*rwhite*), and other or multiracial (*rother*). For BART, respondents are classified as either Hispanic or non-Hispanic. If non-Hispanic, they then select a race. In contrast, for MARTA, Hispanic is a separate category, and respondents are asked to identify both their Hispanic status and their race, allowing them to be categorized as both Hispanic and a specific race. The other variables, with subscripts indicating stations (*s*) or links (*l*), include cost recovery profiles from Equations 5 and 6 (*percentpaid*); the straight-line distance between the subject station or link and the core station (*distancecore*); average trip length in track-kilometers for all trips using the station or link (*triplength*); the total trips using the station or link (*trips*); and, for all OD trips that begin or end at the station or traverse the link, the average straight-line distance their origin and destination stations are from the core station (*decentralization*).

Comparing these statistics with the weighted OD trip statistics in Table 2, the mean cost recovery profiles for stations and links are noticeably lower than the mean for OD trips. Additionally, the standard deviations are smaller, resulting in a narrower spread compared to the OD trip cost recovery data. This difference is mainly due to the different nature of the measurements. Table 2 reflects trip-level cost recoveries for all trips, while Tables 3-5 show the *average* cost recovery for the subset of trips associated with each station or link. As a result, while high-cost recovery OD trips dominate the OD cost recovery statistics, those same OD trips share links and stations with low-cost recovery OD trips. Consequently, even the stations or links with the highest cost recovery profiles will have lower values compared to the highest cost recovery OD trip. Furthermore, high-cost recovery trips may be concentrated on a small subset of stations and links—for example, if many high-cost recovery trips are confined to the urban core. As a result, the remaining stations and links will primarily serve low-cost recovery trips, lowering their cost recovery profiles and reducing the overall average cost recovery profile for stations and links relative to the cost recovery of OD trips. I evaluate this concept in the Results section.

Figure 4 illustrates this pattern. It geographically shows the cost recovery profile of links and stations in the two networks. To illustrate interpretation of these maps, the "average rider" who travels to or from MARTA's Five Points Station pays 34.1% of the costs of their trip, while the "average rider" who traverses BART's link between West Oakland and Embarcadero stations (the Transbay Tube) pays 63.9% of their total trip cost. With few exceptions, this figure suggests that the average cost recovery of riders of different links and stations generally *declines* with distance from each system's core—though, as suggested by the different scales on the maps, the magnitude of variance is significantly less for MARTA relative to BART.

Lastly, the socioeconomic differences between BART's and MARTA's ridership are notable. BART's ridership is "Whiter" and higher income than MARTA's. On average, 61% of the riders at a given BART station have a household income of $60,000 or more, and the racial group with the highest average share at any station is White, with an average of 44% of the station-level ridership. This is nearly twice the share of the secondlargest group, Asian or Pacific Islanders, at 23%. In stark contrast, MARTA's ridership is a "majority-minority" demographic, with 66% of the average station's ridership being Black, and White riders making up a distant 25%. Additionally, MARTA's ridership is generally lower-income, with 57% of riders from households earning less than $50,000, compared to 29% earning $60,000 or more.

Table 3. Descriptive statistics of station profiles—BART

Variable	Minimum	Mean	Median	Standard Deviation	Maximum
$percentpaid_s$	24.86%	54.47%	54.57%	14.36%	99.79%
coredistance (miles)	0 (0)	18.8 (11.68)	15.92 (9.89)	12.44 (7.73)	49.97 (31.05)
$decentralization_s$ (miles)	5.54 (3.44)	15.85 (9.85)	14.02 (8.71)	6.1 (3.79)	31.4 (19.51)
$triplength_s$ (miles)	12.34 (7.67)	27.94 (17.36)	24.54 (15.25)	12.55 (7.8)	67.99 (42.25)
$trips_s$	617,004	4,897,543	3,473,553	5,053,904	24,571,444
rai	0%	0.32%	0.28%	0.2%	0.79%
rapi	9.91%	22.9%	21.9%	9.38%	50.89%
rblack	4%	12.16%	9.76%	7%	36.02%
rhisp	7.88%	17.62%	16.04%	5.89%	37.35%
rother	1.27%	3.39%	3.46%	0.88%	5.2%
rwhite	23.58%	43.61%	45.28%	11.83%	69.51%
i0to25	2.25%	8.31%	7.68%	3.09%	15.17%
i25to35	1.95%	5.23%	5.12%	1.79%	8.9%
i35to40	1.48%	4.87%	4.61%	1.87%	9.33%
i40to50	2.29%	8.47%	7.89%	2.68%	13.71%
i50to60	5.18%	12.36%	12.08%	3.41%	21.34%
i60to75	8.81%	15.24%	15.36%	2.56%	21.11%
i75to100	8.06%	15.21%	15.19%	2.45%	20.08%
i100to150	6.28%	16.08%	16.12%	4.1%	23.23%
i150plus	2.59%	14.22%	12.98%	7.29%	40.82%

N (stations) = 48 (45 for socioeconomic variables)

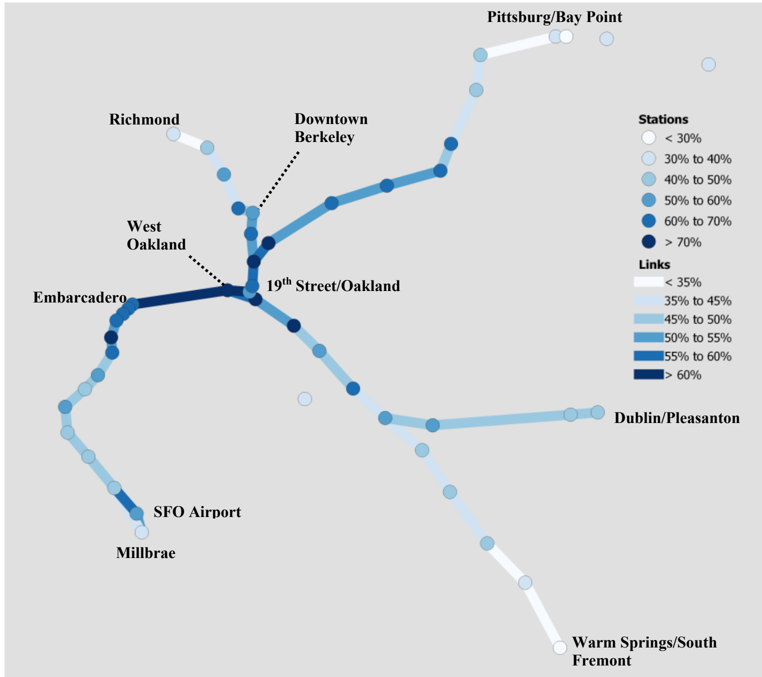
Table 4. Descriptive statistics of station profiles—MARTA

Variable	**Minimum**	**Mean**	**Median**	**Standard Deviation**	**Maximum**
percentpaid$_s$	13.38%	29.37%	29.93%	6.27%	40.71%
coredistance (miles)	0 (0)	9.11 (5.66)	7.61 (4.73)	7.52 (4.67)	25.67 (15.95)
decentralization$_s$ (miles)	4.15 (2.58)	8 (4.97)	6.98 (4.34)	3.01 (1.87)	13.78 (8.56)
triplength$_s$ (miles)	8.08 (5.02)	14.18 (8.81)	12.02 (7.47)	5.17 (3.21)	26.33 (16.36)
trips$_s$	430,987	2,171,240	1,728,397	1,529,423	7,356,599
*rai**	0%	0.96%	0.9%	0.53%	2.45%
*rapi**	0.53%	3.41%	2.4%	2.51%	9.92%
*rblack**	39.2%	66.49%	65.44%	14.59%	89.38%
*rhisp**	2.98%	5.72%	5.22%	2.28%	13.38%
*rother**	0.38%	4.4%	4.19%	2.33%	11.13%
*rwhite**	6.64%	24.74%	25.67%	11.22%	43.86%
*i0to20**	4.96%	15.24%	15.2%	5.26%	26.32%
*i20to30**	4.96%	11.52%	11.43%	3.3%	17.99%
*i30to40**	7.75%	14.83%	14.72%	3.87%	25.57%
*i40to50**	8.68%	15.42%	15.25%	2.95%	19.87%
*i50to60**	8.19%	13.65%	13.9%	2.57%	19.9%
*i60to75**	3.79%	11.5%	11.37%	2.66%	16.27%
*i75to100**	2.83%	8.94%	8.23%	4.27%	20.99%
*i100to120**	0.32%	4.23%	3.63%	2.86%	11.45%
*i120plus**	0.33%	4.67%	3.91%	3.37%	13.02%

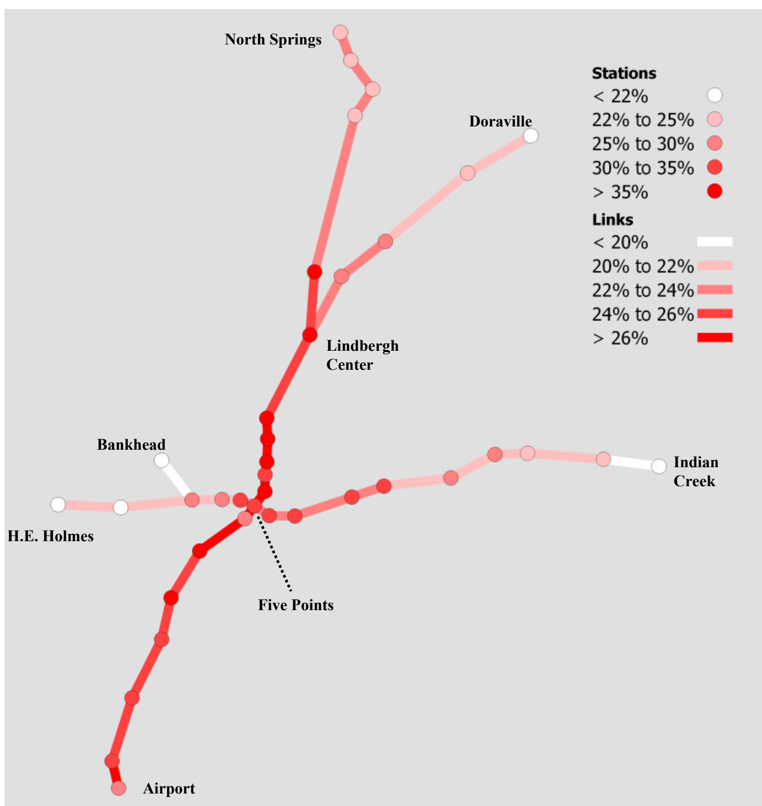
N (stations) = 38
**weighted ARC data*

Table 5. Descriptive statistics of link profiles

Agency	**Variable**	**Minimum**	**Mean**	**Median**	**Standard Deviation**	**Maximum**
BART *N (links) = 47*	*percentpaid*$_l$	13.38%	29.37%	29.93%	6.27%	40.71%
	coredistance (miles)	0 (0)	9.11 (5.66)	7.61 (4.73)	7.52 (4.67)	25.67 (15.95)
	decentralization$_l$ (miles)	4.15 (2.58)	8 (4.97)	6.98 (4.34)	3.01 (1.87)	13.78 (8.56)
	triplength$_l$ (miles)	8.08 (5.02)	14.18 (8.81)	12.02 (7.47)	5.17 (3.21)	26.33 (16.36)
	trips$_l$	430,987	2,171,240	1,728,397	1,529,423	7,356,599
MARTA *N (links) = 37*	*percentpaid*$_l$	13.38%	23.61%	23.83%	2.85%	27.35%
	coredistance (miles)	0.61 (0.38)	9.37 (5.82)	7.72 (4.8)	7.47 (4.64)	25.67 (15.95)
	decentralization$_l$ (miles)	4.83 (3)	9.58 (5.95)	9.27 (5.76)	2.3 (1.43)	13.78 (8.56)
	triplength$_l$ (miles)	10.25 (6.37)	19.76 (12.28)	19.99 (12.42)	3.94 (2.45)	26.67 (16.57)
	trips$_l$	430,987	8,194,683	6,654,606	4,931,187	17,505,807



(A) BART



(B) MARTA

Figure 4. Average cost recovery across links and stations

5.3 Temporal analysis

For the temporal analysis, Tables 6 and 7 present descriptive statistics for different time periods for BART and MARTA, respectively. These data illuminate how variables of interest change across operating time periods.

For five of the variables—cost, fare revenue, cost recovery, trip count, and passenger-kilometers—I report aggregate values for each time period. In FY19, BART's peak period cost $325.4 million to operate and maintain. Unsurprisingly, it was the most expensive time period to run. However, the peak period was also the most productive, serving 63.2 million trips and 1.562 billion passenger-kilometers while recovering 74% of its costs through fares. In contrast, BART's weekday base period cost 79% as much as the peak period but carried only 38% as many trips and 35% as many passenger-kilometers and recovered just 35% of its costs through fares. For MARTA, the peak period cost $86.9 million, served 19.9 million trips and 303.4 million trip-kilometers, and recovered 34% of its costs through fares. In comparison, MARTA's weekday midday period cost about the same but served only 62.2% as many trips and 57.9% as many passenger-kilometers, and recovered just 18.2% of its costs.

For the other variables—average origin and destination station straight-line distance from the core station, and trip length—I show the statistics corresponding to OD trips made during each time period. Hence, the variation in these values reflects how trip consumption patterns vary across time periods. For example, MARTA's weekday peak period has the highest average trip length (15.26 km) of all operating time periods at MARTA, whereas at BART, the weekday peak (24.7 km) ranks third in trip length, behind the weekday evening (25.5 km) and Sunday evening (24.9 km) periods.

Table 6. Temporal descriptive statistics—BART

Time Period		Weekday				Saturday		Sunday/Holiday		Total
		Base	Peak	Evening	Late Evening	Base	Midday	Base	Evening	
$cost_t$ (cost)		\$258,037,518	\$325,430,391	\$67,444,710	\$37,682,645	\$32,792,752	\$53,279,185	\$51,104,798	\$22,027,128	\$847,799,127
$fares_t$ (fare revenue)		\$89,697,710	\$243,146,564	\$35,114,074	\$23,259,610	\$9,622,910	\$22,504,842	\$19,464,467	\$5,878,558	\$448,688,735
$percentpaid_t$ (cost recovery)		34.76%	74.72%	52.06%	61.72%	29.34%	42.24%	38.09%	26.69%	52.92%
$trips_t$ (trips)		24,177,808	63,242,768	8,732,436	6,017,829	2,514,618	6,141,670	5,208,938	1,438,202	117,474,269
***pxkms* (passenger-kilometers)** (passenger-miles)		553,383,117 (343,857,182)	1,562,138,283 (970,670,140)	222,556,382 (138,290,468)	143,939,716 (89,440,215)	59,264,879 (36,825,580)	135,719,431 (84,332,354)	116,428,116 (72,345,257)	35,816,942 (22,255,671)	2,829,246,865 (1,758,016,867)
$triplength_t$ (trip length) (miles)	**Minimum**	0.56 (0.35)				0.56 (0.35)		0.56 (0.35)		0.56 (0.35)
	Mean	22.88 (14.22)	24.7 (15.35)	25.49 (15.84)	23.91 (14.86)	23.56 (14.64)	22.1 (13.73)	22.35 (13.89)	24.9 (15.47)	24.09 (14.97)
	Standard Deviation	16.35 (10.16)	16.03 (9.96)	16.82 (10.45)	16.33 (10.15)	16.11 (10.01)	15.84 (9.84)	15.87 (9.86)	17.06 (10.6)	16.21 (10.07)
	Maximum	91.6 (56.92)				91.6 (56.92)		91.6 (56.92)		91.6 (56.92)
$decentralization_t$ (average O/D station distance from core) (miles)	**Minimum**	1.03 (0.64)				1.03 (0.64)		1.03 (0.64)		1.03 (0.64)
	Mean	13.86 (8.61)	14.19 (8.82)	14.36 (8.92)	14.03 (8.72)	14.05 (8.73)	13.73 (8.53)	13.94 (8.66)	14.58 (9.06)	14.1 (8.76)
	Standard Deviation	6.73 (4.18)	6.6 (4.1)	6.92 (4.3)	6.92 (4.3)	6.82 (4.24)	6.6 (4.1)	6.69 (4.16)	7.07 (4.39)	6.68 (4.15)
	Maximum	47.97 (29.81)				47.97 (29.81)		47.97 (29.81)		47.97 (29.81)

Table 7. Temporal descriptive statistics—MARTA

Time Period		**Weekday**			**Weekend/Holiday**		**Total**
		Base	**Peak**	**Evening**	**Base**	**Midday**	
$cost_t$ (cost)		$86,991,391	$86,950,887	$14,582,218	$43,032,908	$6,435,315	$237,992,718
$fares_t$ (fare revenue)		$15,839,966	$29,559,350	$2,626,714	$9,450,864	$1,099,602	$58,576,496
$percentpaid_t$ (cost recovery)		18.21%	34%	18.01%	21.96%	17.09%	24.61%
$trips_t$ (trips)		12,391,117	19,898,647	2,057,750	6,985,699	841,506	42,174,719
***pxkms* (passenger-kilometers)** (passenger-miles)		175,750,870 (109,206,799)	303,437,447 (188,547,757)	27,794,211 (17,270,565)	98,987,381 (61,508,060)	11,228,452 (6,977,054)	617,198,362 (383,510,235)
$triplength_t$ (trip length, kilometers) (miles)	**Minimum**		0.61 (0.38)		0.61 (0.38)		0.61 (0.38)
	Mean	14.18 (8.81)	15.26 (9.48)	13.5 (8.39)	14.16 (8.8)	13.34 (8.29)	14.63 (9.09)
	Standard Deviation	10.01 (6.22)	9.56 (5.94)	9.43 (5.86)	9.72 (6.04)	9.32 (5.79)	9.72 (6.04)
	Maximum		43.34 (26.93)		43.34 (26.93)		43.34 (26.93)
$decentralization_t$ (average O/D station distance from core, kilometers) (miles)	**Minimum**		0.29 (0.18)		0.29 (0.18)		0.29 (0.18)
	Mean	7.97 (4.95)	8.3 (5.16)	8.24 (5.12)	7.9 (4.91)	8.03 (4.99)	8.13 (5.05)
	Standard Deviation	4.41 (2.74)	4.28 (2.66)	4.12 (2.56)	4.26 (2.65)	4.09 (2.54)	4.31 (2.68)
	Maximum		20.73 (12.88)		20.73 (12.88)		20.73 (12.88)

6 Results—spatial analysis

Table 8 presents the results of the OD cost recovery model, which examines how trip length and the average straight-line distance of the origin and destination stations from the core station (*decentralization*) influence cost recovery across OD pairs. As outlined in the Data and Methods section, *triplength* represents the distance element of cost recovery, while *decentralization* accounts for the geographic variation in cost recovery due to how much a trip is centered around the urban core. In Table 8, I report results in both base units (i.e., kilometers) and standard normal units, applying robust standard errors.

Below, I interpret these results with particular attention to the differences between BART's monocentric travel patterns and MARTA's more polycentric-to-dispersed travel patterns and their implications. I then scale the findings to stations and links to assess the spatial incidence of subsidies, before discussing the resulting socioeconomic implications.

Table 8. Origin-destination cost recovery model results

Agency	Variable	Coefficient		Standard Error (Robust)	95% Confidence Interval
	Base / Standard Normal (SN)	**Base**	**SN**		
BART	*ln(triplength)*	-0.04*	-0.082*	0.021	(-0.081, 0.002)
N (two-way OD pairs) = 1,124	*ln(decentralization)*	-0.409***	-0.556***	0.031	(-0.47, -0.349)
R-squared: 0.3729	*constant*	4.777***		0.058	(4.663, 4.89)
MARTA	*ln(triplength)*	-0.44***	-0.898***	0.021	(-0.481, -0.399)
N (two-way OD pairs) = 703	*ln(decentralization)*	0.136***	0.243***	0.023	(0.091, 0.182)
R-squared: 0.5183	*constant*	4.003***		0.031	(3.943, 4.063)

Statistical Significance: *** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.1$

6.1 OD trip cost recoveries

In both the MARTA and BART systems, trip length is negatively associated with cost recovery (i.e., longer trips receive more subsidy), though the magnitude of this effect is markedly greater for MARTA. At BART, a 1% increase in trip length is associated with a 0.04% *decrease* in cost recovery. For MARTA, the impact is eleven-fold; a 1% increase in trip length corresponds to a 0.44% *decrease* in cost recovery. However, the relationship between cost recovery and OD decentralization scores differs between the two networks. For BART, a 1% increase in the decentralization score is associated with a 0.41% *decrease* in OD cost recovery, whereas MARTA sees a 0.14% *increase*. Beyond the differing directions and magnitudes, *decentralization* has greater statistical significance than trip length in explaining OD trip cost recovery for BART, whereas both independent variables are statistically significant at the $p \leq 0.001$ level for MARTA. As I discuss below, these contrasting results may be attributed to the distinct travel patterns in the two systems: BART is characterized by heavily monocentric travel patterns, in contrast to MARTA's weaker core and more prominent peripheral nodes of travel activity.

Focusing on *decentralization*, these results suggest that "suburban" travelers in the MARTA system—those whose origins or destinations are further from the core—are *less* subsidized than their urban counterparts when trip length is controlled for. Thus, to the extent that suburban travelers receive more subsidies, it appears to be a function of trip length rather than proximity to the core. This challenges a central hypothesis of this research: that trip costs vary by location relative to the core and that fare structures failing to account will produce geographic disparities in cost recovery. Yet, as seen in Figure 3, there exists a clear logarithmic negative correlation between an OD pair's decentralization score and cost recovery in both systems (-0.607 for BART and -0.47 for MARTA), significant at the $p \leq 0.001$ level.

The regression results for MARTA may be explained by how its fare structure interacts with MARTA's dispersed travel patterns. First, as previously discussed, BART's travel patterns are heavily core-oriented—two thirds of all trips begin or end in downtown San Francisco and a plurality of trips associated with every station begin or end in downtown San Francisco. As a result, BART experiences low costs per rider in the core that increases towards the periphery as ridership tapers off (Mallett, 2022). Without a fare structure that controls for this, a strong negative relationship between decentralization and cost recovery is expected. In stark contrast, MARTA's core is weaker, which will diminish the explanatory power of decentralization. This is reflected in the lower one-to-one correlation and the reduced cost recovery variance in Figure 4.

Compounding this, several outliers in Figure 3(b) are high-cost-recovery OD pairs associated with travel nodes distant from downtown Atlanta—specifically, near the airport in the south and employment subcenters in the north. Additional outliers are low-cost-recovery OD pairs associated with travel along the Bankhead branch of service that is geographically proximate to downtown Atlanta but has the lowest ridership and highest cost per rider in the network. Thus, in addition to the central business district (CBD) not being a particularly strong epicenter of travel activity for MARTA, the system also has relatively strong peripheral nodes of travel activity and depressed travel activity in areas near the CBD. This further diminishes the core-orientation of travel, so may further reduce the role of *decentralization* in explaining cost recovery.

Finally, MARTA's flat-rate fare structure may further diminish the role of *decentralization* by the way it interacts with the system's dispersed travel environment. Flat-rate fares, by definition, do not account for the distance element of transport costs, which is reflected in the dependent variable's strong negative relationship with trip length. However, this relationship can be amplified, and the role of *decentralization* diminished, in an environment where travel and cost-per-rider patterns are less spatially variable. In such an environment where geography-based costs are relatively flat, the spatial incidence of subsidies from flat-rate fares will be driven primarily by trip length rather than where travel occurs. This aligns with the implicit assumptions of Brown (2018) and Cervero (1981), at least in environments where travel and costs are highly dispersed. The culmination of these dynamics—dispersed travel patterns, weak core-centrality, strong peripheral travel centers, and flat-rate fares—may explain the opposing role that OD pairs' decentralization scores play in MARTA's regression results. Specifically, the regression model compensates for the weaker core-orientation by assigning a positive coefficient to *decentralization*, which is then offset by an amplified negative impact of trip length.

Diagnosing this using the current model by removing OD outliers cannot be done robustly without excluding the OD outliers in each iterative step—including cost per rider estimations, OD trip cost estimations, and others—and then re-running the regression analysis. This is because OD cost recovery calculations are interdependent on the travel patterns of all other OD pairs. To comprehensively investigate this hypothesis, future research might consider expanding the model by incorporating multiple *decentralization* variables to account for different nodes of travel activity—for example, adding a second *decentralization* term for Buckhead, the northern job center. Even in the case of BART, I chose West Oakland Station as the core station because it is the point of ridership crush load and is the one stop that separates downtown Oakland and downtown San Francisco. Designating separate *decentralization* variables for downtown Oakland and downtown San Francisco may improve the model's accuracy.

Unlike MARTA, BART's results mostly align with my original hypotheses. The results suggest that, when the decentralization of travel is controlled for, distance-based fares attenuate but do not eliminate the relationship between trip length and subsidies. On face value, this conflicts with my hypothesis; in theory, a distance-based fare structure will account for the distance element of costs, leading to a null or statistically insignificant regression result for trip length. One possible explanation is that the per-unit price is set too low to fully recover the distance-based costs of service. In addition, while trip length and decentralization scores are not inherently collinear, their correlation increases at longer trip distances, as longer trips are more likely to involve origins and destinations that are both located far from the core. This may positively influence how the model accounts for trip length. Finally, BART's distance-based fare structure follows a stepwise model that reduces the per-mile cost as distance increases, diminishing recovery of any distance-related expenses for longer trips. Nonetheless, the influence of trip length on cost recovery remains relatively small: a 1% increase in trip length is associated with a 0.04% decrease in cost recovery, with limited statistical significance at a $p \leq 0.1$ level. This supports my original hypothesis that distance-based fares mitigate the impact of transport costs related to trip length, but do not fully account for all trip costs. The decentralization findings further highlight this, showing that distance-based fares fail to capture the geography-based element of costs—particularly in monocentric systems like BART, as discussed earlier.

Taken together, these findings suggest that decentralization scores' effect on OD cost recovery depends on both fare structure and travel patterns. Whereas BART employs a stepwise distance-based fare structure, MARTA uses a flat-rate system, and neither incorporate a component that accounts for geography. In BART's monocentric system, the absence of a geography component in their fare structure is associated with lower cost recovery for decentralized trips. In contrast, MARTA's weaker core-periphery gradient of travel demand and costs per rider suggest that a geography-based fare component may not have a strong rationale in its fare structure to begin with. Instead, in such systems, cost recovery dynamics—at least when the fare structure is flat-rate—appear to be driven more by trip length than where travel occurs.

Finally, while other variables like OD ridership and station costs were explored to enhance the model, they are collinear with the existing variables. Future research may develop instruments to address this limitation.

6.2 Station and link cost recovery profiles

Whereas the preceding analysis examines whether longer or more "suburban" *trips* are disproportionately subsidized, this subsection investigates whether these disparities in trip-level cost recovery translate into geographic disparities in subsidy distribution. In other words, do certain geographic communities receive more transport subsidies, on average? To explore this, I calculate the average cost recovery for *all* trips that begin or end at a station, as well as for *all* trips that traverse a link (see Equations 5 and 6). I emphasize "all" because, unlike the OD trip regressions—which reflect the cost recovery of one trip given how each system is built, operated, and used—the station- and link-level analysis weights for trip frequencies to capture the net geographic incidence of subsidies. Once I derive these "cost recovery profile" scores, I correlate them with the weighted average trip length (*triplength*) and decentralization score (*decentralization*) of trips using each station or link (with subscripts "s" and "l" corresponding to unique stations and links, respectively), along with the straight-line distance each station and link is from the core station (*coredistance*). Figures 5 and 6 visualize these relationships for stations and links, respectively, while Table 9 summarizes the correlation results.

Table 9. Station and link cost recovery profile correlations

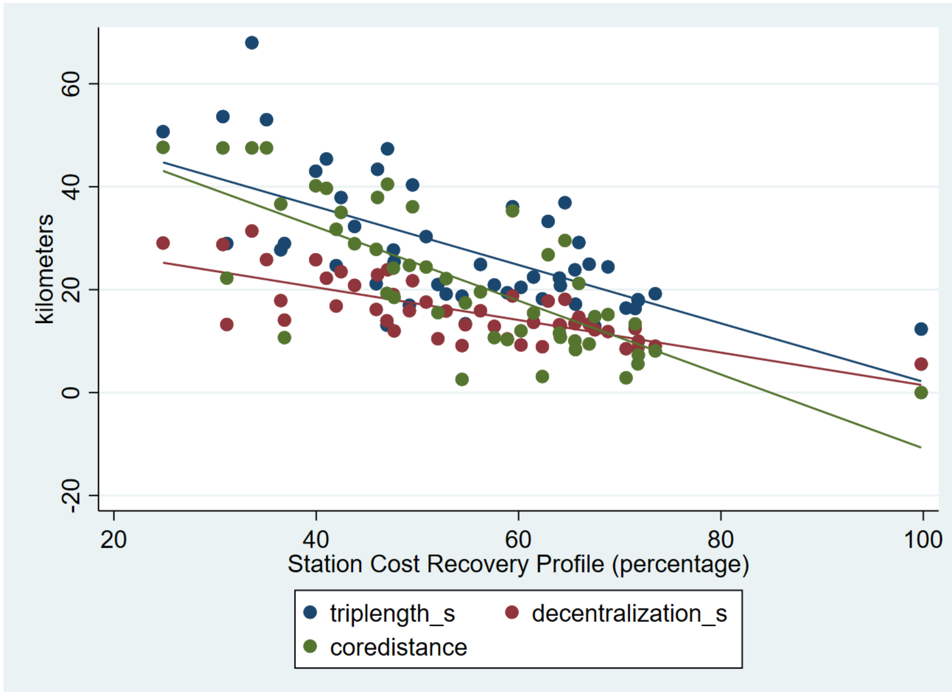
Agency	Variable	Stations	Links
BART	*coredistance*	-0.759***	-0.669***
	$decentralization_s$ / $decentralication_l$	-0.745***	-0.617***
	$triplength_s$ / $triplength_l$	-0.649***	-0.462**
MARTA	*coredistance*	-0.492***	-0.184
	$decentralization_s$ / $decentralication_l$	-0.375*	0.263
	$triplength_s$ / $triplength_l$	-0.438***	0.428**

Statistical Significance: *** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.1$

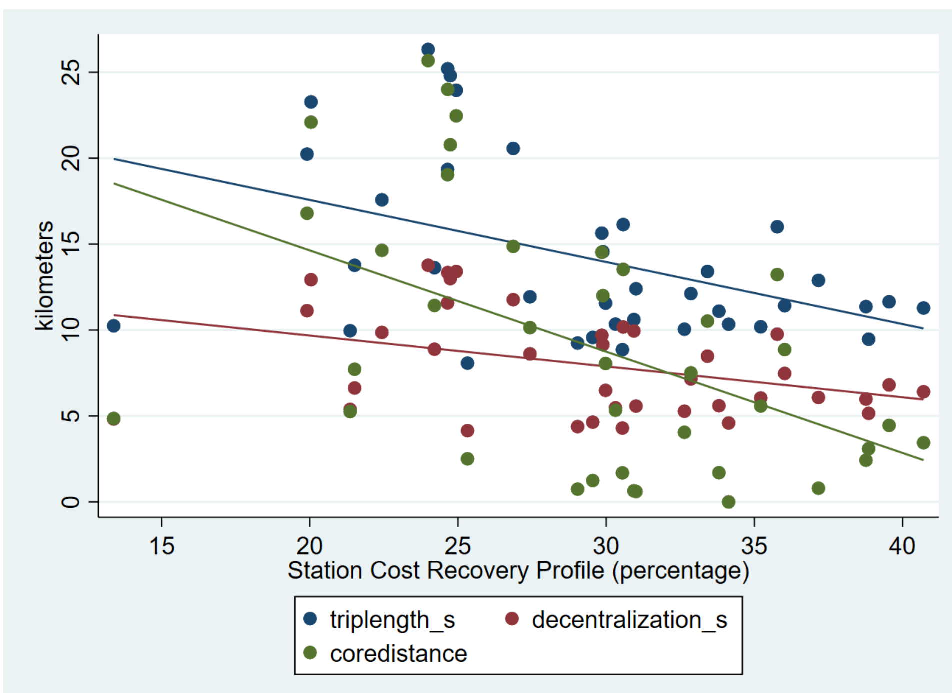
The correlations mostly align with my hypotheses: links and stations that are farther from the urban core, serve longer-distance trips, and are more associated with peripheral travel tend to have lower cost recovery profiles, on average. For BART stations, cost recovery profiles are negatively correlated with the distance of each station from the core station (-0.76), the average length of trips using the station (-0.65), and the average decentralization score of trips using the station (-0.75), all statistically significant. For BART links, the correlations are -0.46, -0.62, and -0.67, respectively, with all values also statistically significant. Similarly, for MARTA stations, the correlations are -0.44, -0.38, and -0.49, respectively, all statistically significant. An anomaly arises for MARTA links, however, where cost recovery profile shows a statistically significant *positive* correlation with the average trip length of trips using those links (0.43), contrary to my hypotheses. There is no statistically significant correlation between cost recovery profile and the other variables for MARTA links.

Beyond assessing how these correlations compare to my hypotheses, the patterns in MARTA's station and link cost recovery profiles appear inconsistent with the OD trip-level findings. The OD trip regression results indicate a strong negative relationship between OD trip length and cost recovery, along with a moderate positive association between OD decentralization scores and cost recovery. Yet, when aggregated to the station level, stations serving trips with higher average decentralization scores exhibit *lower* average cost recovery. Similarly, at the link level, links that serve longer trips are associated with *higher* cost recovery—again, contrary to the OD trip regression results.

Several factors may explain the discrepancy between the OD trip-level analysis and the aggregate station- and link-level results for MARTA, particularly the weighting of station and link data and the system's unique travel patterns. First, moving from disaggregate OD trip data to aggregate station- and link-level data inherently averages out trip-level nuances. While trip lengths and decentralization scores may have one relationship with cost recovery at the trip level, their aggregate effects at stations and links depend on actual (i.e., weighted) trip consumption patterns. If certain OD trips are disproportionately concentrated at particular stations, the relationship between these variables and station-level cost recovery will diverge from the OD trip-level findings. For example, MARTA's highest-ridership OD pair, which has 1.4 times as many trips as the second-highest ridership OD pair and is the only OD pair with over 100% cost recovery, is between Airport and College Park stations—its two southernmost stations.

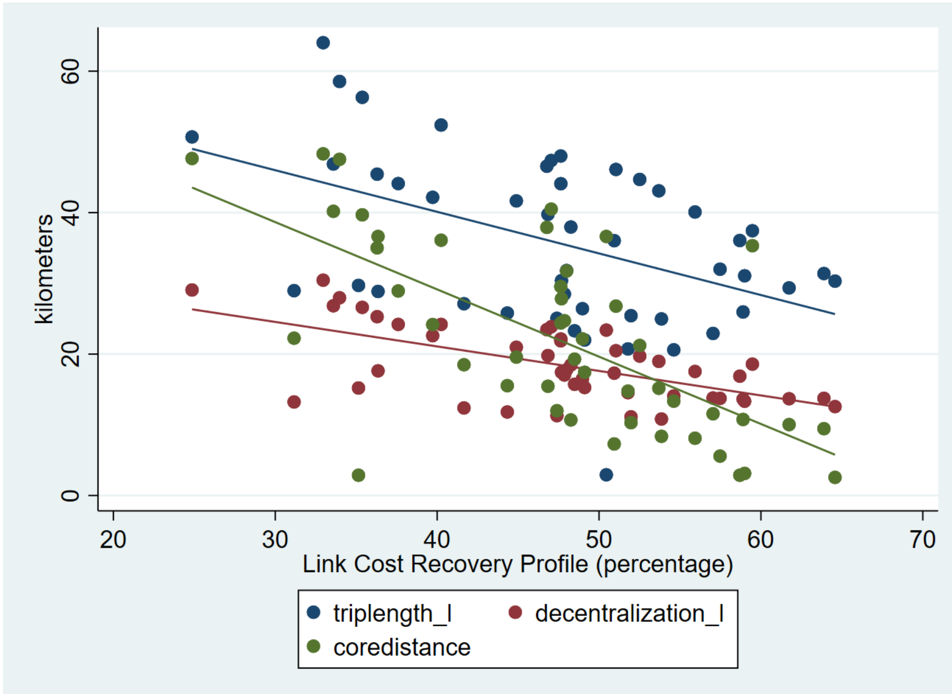


(A) BART

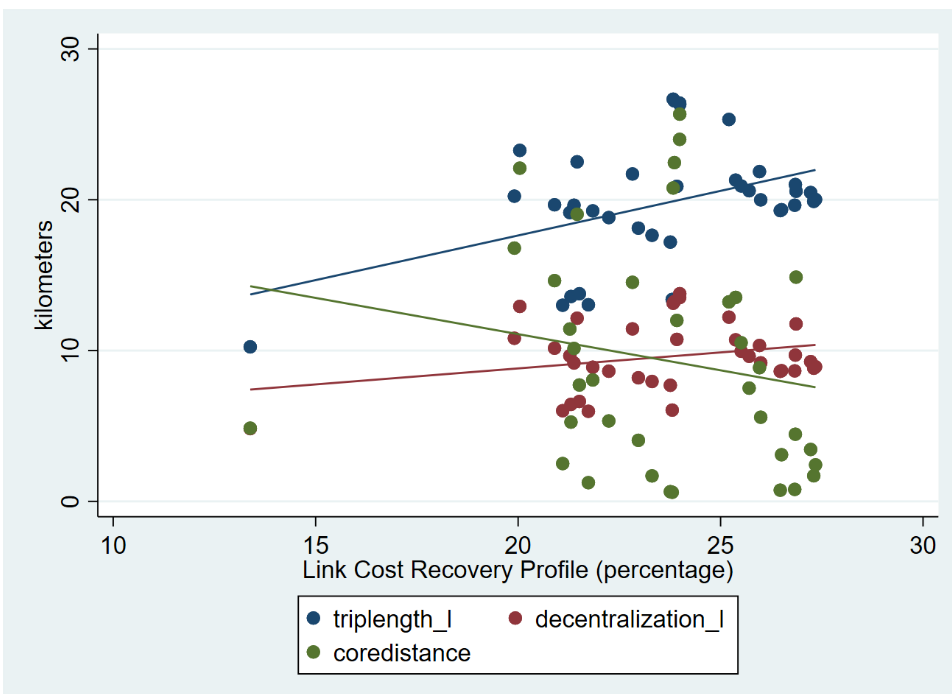


(B) MARTA

Figure 5. Station cost recoveries and spatial variables



(A) BART



(B) MARTA

Figure 6. Link cost recoveries and spatial variables

6.3 Socioeconomic impacts

As these stations are distant from the core station, this OD pair has a high decentralization score, which can positively influence the relationship between station cost recovery profiles and average trip decentralization scores. Links are particularly sensitive to this "weighted average" effect since they serve more OD pairs than stations do. Of the 14 links (37%) with a cost recovery profile exceeding 25%, most are located at least four stations north or south of Five Points Station, and all serve trips averaging at least 19 kilometers (approximately 12 miles)—1.23 times the unweighted average and 1.29 times the weighted average (see Table 2). Thus, while Table 2 shows that MARTA's weighted OD trip distributions closely resemble their unweighted distributions—supporting the OD trip regression results—the way these distributions manifest across stations and links differs.

In contrast, BART's station and link cost recovery profiles are consistent with the OD trip cost recovery regression results. Stations and links further from the core, serving longer-distance and more decentralized trips, show lower cost recovery, on average. For example, of the 17 (36%) links with the highest cost recovery profiles, 16 are continuously adjacent to the core station, and all but one of the 22 OD pairs with over 100% cost recovery involves travel to, from, or within downtown San Francisco. This is consistent with the monocentric travel pattern at BART.

One last important observation between the two systems relates to their *inequitable inefficiency*. While BART is more efficient than MARTA overall, recovering a greater share of its costs through fares (see Table 1), the geographic cost recovery patterns in the two systems notably differ. In particular, MARTA's inefficiency is more geographically equitable with less variation in cost recovery profiles across stations and links compared to BART (though the scale of these differences is less obvious in Figures 5 and 6 due to the differing ranges of the x-axes). In contrast, BART shows greater spatial variability in cost recovery profiles, with a more pronounced cross-subsidization effect where core-oriented trips subsidize suburban and exurban travel. This difference may be partially attributed to the combination of BART's stepwise distance-based fare structure not accounting for geography-based costs despite its monocentric travel patterns. By contrast, MARTA's flat-rate fare structure, in combination with its polycentric-to-dispersed travel pattern, may contribute to a more even distribution of inefficiency across its network.

To understand the socioeconomic incidence of subsidies, I analyze pairwise correlations between station cost recovery profiles and the shares of different socioeconomic groups of riders at each station. I also analyze how these socioeconomic characteristics relate to other station-level attributes, including the average trip length ($triplength_s$) and average decentralization score ($decentralization_s$) of all trips associated with each station. The results are shown in the correlation matrix in Appendix A, where cells shaded blue correspond to BART and those shaded red correspond to MARTA. In the following discussion, I summarize only statistically significant correlations.

In both networks, among income groups, only the share of riders with a household income between \$60,000 and \$75,000 (*i60to75*) has a statistically significant correlation with station cost recovery profiles ($percentpaid_s$). However, the relationships are moderate and opposite in direction: -0.4 at BART and 0.36 at MARTA. For racial groups, station cost recovery profiles in the BART system correlate negatively with the share of riders who identify as Asian or Pacific Islander (*rapi*, -0.41) and Hispanic (*rhisp*, -0.34), but positively with the share of riders who identify as Non-Hispanic White (*rwhite*, 0.4). This suggests that, at least on a racial basis, the distribution of subsidies at BART may have slightly progressive effects—contrary to prior research that suggests transit subsidies tend to be racially regressive (e.g., Cervero, 1981). No statistically significant racial correlations with station cost recovery profiles emerge for MARTA.

Several relationships between socioeconomic variables and spatial attributes of stations are consistent across both networks. Stations with longer average trip lengths and more "suburbanized" trip patterns—reflected in higher average trip decentralization scores—are associated with higher shares of riders in upper-income categories and lower shares of riders in lower-income categories. Correlations for decentralization scores range from 0.31 to 0.6 for higher-income category shares and -0.27 to -0.51 for lower-income category shares; for trip length, they range from 0.36 to 0.56 and -0.28 to -0.6, respectively. These patterns align with established research: longer and more suburban-oriented trips are typically associated with higher-income persons, particularly if they use transit (Brown, 2018; Cervero, 1981; Morris & Zhou, 2018; Pucher & Renne, 2003; Wang & Renne, 2023). Lastly, decentralization scores also positively correlate with the share of riders who identify as Asian or Pacific Islander in both networks (0.46 at BART and 0.52 at MARTA).

Other socioeconomic-spatial relationships differ between the systems. At MARTA, the average decentralization scores for trips served by a station are positively correlated with the shares of riders who identify as Mixed or Other (*rother*, 0.46), White (0.4), or Hispanic (0.46), but negatively correlated with the shares of riders who identify as Black (*rblack*, -0.39). Similarly, the longer the average trip served by a stations, the higher the share of riders who identify as Asian or Pacific Islander (correlation of 0.5), Mixed or Other (correlation of 0.5), White (correlation of 0.43), or Hispanic (correlation of 0.45), but the lower the share of Black riders (correlation of -0.5). In contrast, at BART, the average decentralization score is positively correlated with the share of riders identifying as Asian or Pacific Islander (0.46) and negatively correlated with the shares of White (-0.26) and Mixed or Other (-0.31) riders. At BART, average trip length has no statistically significant correlation with racial group shares.

These findings reveal an ambiguous relationship between socioeconomics and geographic subsidy patterns, particularly with respect to income. First, as discussed in the preceding subsection and reaffirmed in the correlation matrix, outlying stations tend to have lower cost recovery profiles, meaning riders at these stations typically receive higher rates of subsidy. Second, while both average trip length and average trip decentralization score correlate positively with the share of a station's riders classified in upper-income groups and negatively with station cost recovery profiles, the share of riders in upper-income groups itself has no statistically significant direct relationship with station cost recovery profiles. Thus, while higher-income riders appear to take longer and more decentralized trips—patterns associated with lower cost recovery profiles—the correlation between income and subsidies is not straightforward or consistent across stations. Figure 7 illustrates these relationships. One possible explanation is that higher-income riders who use stations with low-cost recovery profiles disproportionately benefit from subsidies—because their trips tend to be longer and more decentralized—but represent a small share of the overall higher-income rider population, which dampens the relationship between income and station cost recovery profiles. Alternatively, higher-income riders may disproportionately benefit from subsidies at stations with lower cost recovery profiles due to their longer, more decentralized trips. However, the presence of middle- and lower-income riders—who tend to take shorter, more centralized trips—at these same stations may obscure a direct income-subsidy relationship. Similar gaps in understanding exist for select racial groups—for Asian and Pacific Islander riders in both networks and for Mixed/Other, White, and Hispanic riders at MARTA. A comprehensive understanding would require trip-level socioeconomic data, which is unavailable with the data used in this research.

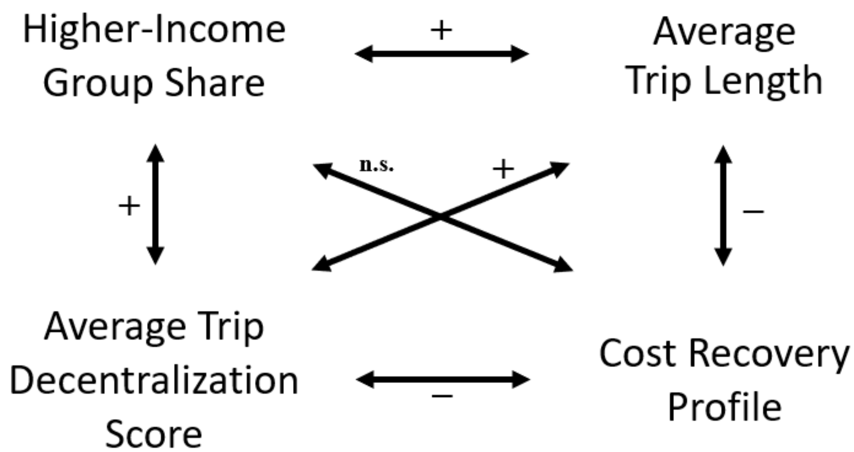


Figure 7. Correlation diagram between average trip length, average decentralization score, cost recovery profile, and upper-income group share

Overall, these findings emphasize the nuanced relationship between the spatial incidence of transit subsidies and their socioeconomic implications. While it is clear that stations serving longer and more decentralized trips tend to have lower cost recovery profiles, the socioeconomic composition of ridership at these stations complicates a direct relationship between income and subsidies. Additionally, because these findings rely on station-level aggregates, they may obscure travel patterns of individual socioeconomic groups (i.e., the ecological fallacy). Different demographic groups at each station may consume different OD pair trips, so what holds true for a station's average ridership may not necessarily apply to each group within it. Further research, with access to trip-level socioeconomic data, would be needed to fully disentangle these patterns.

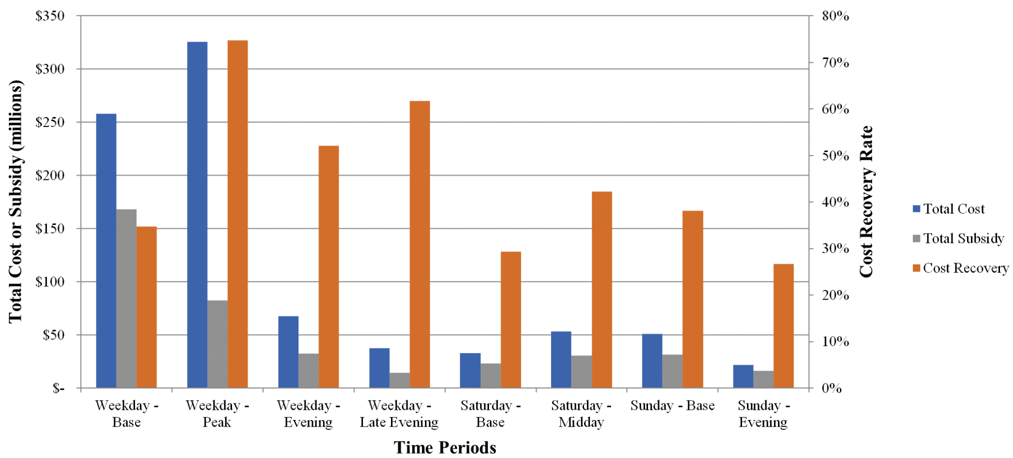
7 Results—temporal analysis

In this section, I focus on the temporal patterns of cost recovery (and subsidies). Specifically, I explore how cost recovery differs across operating time periods at BART and MARTA and how these trends interact with travel patterns.

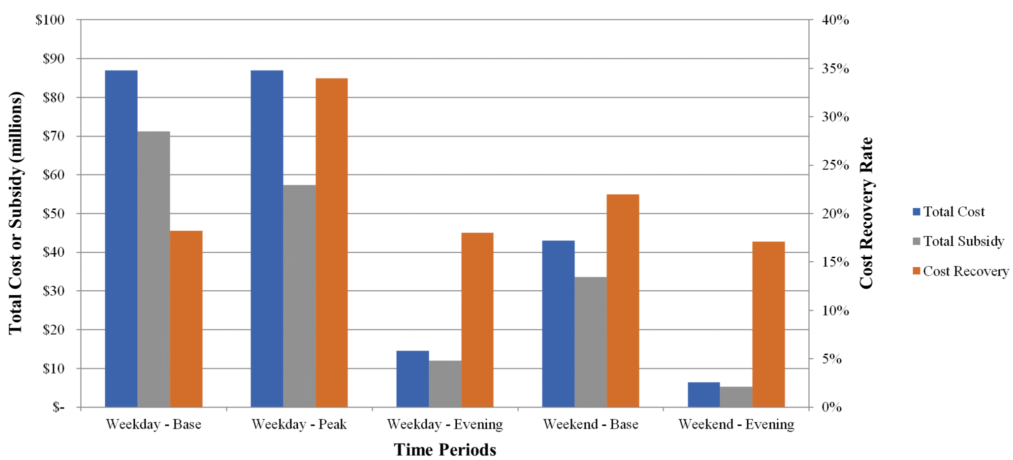
Although the weekday peak period is the most expensive to serve for BART and about as costly as the weekday base period for MARTA, it recovers the highest proportion of its costs through fare payment in both systems—75% at BART and 34% at MARTA. However, proportions do not tell the full story; a time period can still receive more monetary subsidies even if it recovers a higher share of costs. Yet, the weekday peak period in both systems recovers twice the share of its costs compared to the weekday base period—so much so that even the monetary subsidy weekday peak service receives is less than weekday base service. This holds true even after accounting for semi-fixed asset costs, including, for example, BART's peak period being solely responsible for the annualized purchase price of 37% of the agency's railcars and responsible for 57% of the overall annualized purchase price of railcars through its proportional usage (Mallett, 2022). Thus, contrary to prior studies that find the peak period receives the most subsidies (Cervero, 1981; Parody et al., 1990), I find it is the least subsidized. As I elaborate in the discussions section, this may be explained by a combination of cost allocation methods and the fact that I focus on heavy rail transit systems rather than bus systems (Cervero, 1981) or the aggregate of all United States transit operations (Parody et al., 1990).

Other time periods' total and marginal costs—that is, the additional costs of serving a time period relative to the next-highest-cost time period—are much smaller compared to weekday base and peak periods. Even so, it is noteworthy that the weekend base period at MARTA and Sunday base period at BART also have higher cost recoveries than the weekday base period. These findings are reflected in Figure 8, which shows total costs allocated (left axis), cost recovery (right axis), and resulting monetary subsidy (left axis) of different time periods in the BART and MARTA systems.

Finally, in running a pairwise correlation of the relationship between cost recovery and select travel pattern variables *across time periods*, I find that cost recovery ($percentpaid_t$) has a statistically significant positive association with trip counts ($trips_t$) and trip-kilometers (passenger-kilometers, *pxmiles*) in both systems. These correlations are 0.39 and 0.7 for BART, and 0.84 and 0.86 for MARTA, respectively. However, the relationship between cost recovery and trip-kilometers—essentially the product of average trip length and trip count—appears to be explained differently in the two systems. For BART, the correlation between cost recovery and trip-kilometers is fully accounted for by trip count, meaning that in time periods with higher trip counts, the average trip length doesn't significantly increase. In contrast, for MARTA, average trip length plays a key role in explaining the correlation, with longer trips contributing to both higher cost recovery and greater trip-kilometers. Specifically, in the MARTA network, average trip length ($triplength_t$) has a strong positive correlation with cost recovery (0.92), trip counts (0.97), and trip-kilometers (0.98) across time periods. Thus, time periods with longer average trips also tend to recover more costs and serve more trips, which in turn generates more trip-kilometers. On the other hand, travel centrality around the urban core ($decentralization_t$) does not appear to have a strong relationship with temporal cost recovery patterns in either network. Thus, to the extent cost recovery is influenced by how "suburban" a trip is, this influence does not vary across time periods. Appendix B presents these findings, with BART highlighted in blue and MARTA in red, as before.



(A) BART



(B) MARTA

Figure 8. Costs, subsidies, and cost recoveries by time period

8 Discussion and conclusion

In the preceding analysis, I measured the spatial and temporal incidence of travel subsidies in the BART and MARTA networks and found that trips less concentrated around the urban core and during off-peak travel times tend to be associated with higher levels of subsidy. This finding is consistent with commonly rationalized views in practice, which suggest that urban and peak period services generate greater ridership and fare revenue than suburban and off-peak services and are thus less subsidized. However, my findings do not align with prior empirical studies that suggest the peak period is much more costly to serve than off-peak periods, and that ridership and fare revenue do not compensate for these higher costs. In addition, when OD cost recoveries are weighted to trip count and averaged at the station level, I find that subsidy patterns are moderately progressive, which is also contrary to past studies. As I explain below, my contrary findings are likely explained by a combination of differences in the spatial and temporal granularity of analysis, modes of transit analyzed, and types of asset costs included in cost allocations.

8.1 Spatial analysis

One key objective of this research is to challenge the assumption that the amount of travel alone explains cost and subsidy patterns (e.g., Brown, 2018; Cervero, 1981), by evaluating whether the *where* of travel—rather than just the distance—matters in determining cost recovery equity. I contend that trips further from urban activity centers have fewer riders to share costs with, and a constant cost per kilometer rate fails to account for this.

My regression analysis for BART supports this hypothesis: trips less concentrated around the urban core explain subsidy patterns more than trip length, both in terms of statistical significance and magnitude. This finding challenges the conventional view that trip length is the dominant factor in explaining subsidies. For MARTA, although the regression analysis suggests that less core-oriented OD pairs tend to be *less* subsidized, this is likely explained by the model not accounting for activity centers outside downtown Atlanta. Indeed, the one-to-one relationship between cost recovery level and core-centrality is negative. And when aggregate patterns in the networks (weighted OD trips) are averaged at the link and station level, I find that trips associated with outlying links and stations are associated with higher levels of subsidy than trips associated with inner links and stations, on average.

For policy, this suggests that if cost recovery parity is an objective, a combination of distance-based and zonal fare structures may be warranted. However, the dispersion of travel patterns in a network would need to be controlled for when calibrating this balance. Heavily monocentric systems, like BART, would assign more weight to zonal factors than systems whose ridership is more dispersed, like MARTA.

In addition, outward growth continues to be an ever-present concern in transportation and land use policy, with practitioners, policymakers, and scholars seeking to mitigate the negative environmental impacts of sprawl. Urban economic theory proposes that lower generalizable costs of travel will induce outward growth as individuals substitute between land and transportation costs (e.g., Alonso, 1964; Mills, 1967; Muth, 1969). Some literature suggests that highways facilitated outward growth (e.g., Baum-Snow, 2007). Further research is warranted to investigate if transport subsidies, including of transit, as opposed to the mere existence of transportation infrastructure, influences sprawl. The findings from this research that BART and MARTA rider subsidies seem to flow to outer areas of their networks supports further investigation of this.

Finally, my findings on the socioeconomic incidence of subsidies have mixed consistencies with past research. Many scholars find that flat fares are regressive on income and racial bases because of disparities in the effective cost per mile paid (Brown, 2018) or cost recovery across geographies (e.g., Cervero, 1981). My measurement of equity (incidence of subsidy) is most closely aligned with Cervero (1981). My findings are consistent in that I find that BART, an agency with distance-based fares, has cost recovery patterns that are progressive; some marginalized racial groups consume travel through stations with low-cost recovery profiles, while persons who identify as White consume more travel through stations with high-cost recovery profiles, on average. On the other hand, with MARTA, a flat rate fare system, I find no cost recovery disparity across racial groups, despite finding that Black riders consume shorter and more urban-centric travel. Potential sources of difference in findings include my use far more granular units of analysis (i.e., OD trip cost recoveries scaled to stations) and focusing on rail transit as opposed to bus transit. As acknowledged previously, the ecological fallacy caveat applies; what is true about stations' populations may not be true about segments of that population.

8.2 Temporal analysis

In my temporal analysis, I calculated the cost recovery for various operating time periods by dividing aggregate fares by allocated costs. I find that the weekday peak period, while the costliest to operate for BART and about as costly as the weekday base period for MARTA, is the most efficient in both networks. This contradicts the prevailing findings in past research, such as those by Cervero (1981) and Parody et al. (1990), which show that the peak period is the costliest to serve even after accounting for cost recovery. Plausible explanations for this divergence include how fixed costs are treated in cost allocations, the level of commuter service peaking at BART and MARTA compared to other systems, the different mode of transit focused on, and the granularity in time periods studied.

As discussed in the literature review, most of the research on cost recovery disparities is quite old and primarily focused on bus transit. In this research, I focused on BART and MARTA rail transit, which has more capital and maintenance-intensive costs than bus service, as rail operators must maintain their own right-of-way. This may reduce the cost difference between peak and off-peak times by having the effect of increasing the role of variable costs. More significantly, BART and MARTA operate relatively fixed headways throughout the day, which reduces the peak-to-base cost differential compared to systems that do not prioritize maintaining fixed headways. Depending on your perspective, this either greatly reduces the relative cost of peak service or greatly increases the relative cost of off-peak service. Finally, effectively all prior research on temporal variation in costs or cost recoveries use peak and off-peak service categories, which oversimplifies the number of time periods that transit operators scale service output for. In my study, I found that BART and MARTA have eight and five operating time periods that they scale to, respectively, and evaluate temporal variability across each of these.

Accordingly, some generalizable takeaways are that the temporal patterns of costs and cost recoveries are likely contingent on how "peaky" peak period service output is. The flatter it is, the less likely the peak period will be disproportionately subsidized compared to off-peak periods. A growing equity argument for more off-peak service is that there is no marginal cost to providing it because assets sit unused otherwise. However, the BART and MARTA experiences show this is false because increasing off-peak service levels converts solely peak period costs (e.g., railcars that would otherwise be in storage) into shared costs without the ridership and fare revenue to offset it. Finally, if cost recovery equity is an objective in fare policy, these findings suggest that charging the peak period *less* would be more equitable—though, as I explain below, there may be overriding considerations that I did not investigate and warrant further research.

8.3 Other considerations

While this research suggests that core stations and links, as well as the weekday peak period, are less subsidized than suburban stations and links or other time periods—implying that urban stations and peak travel should be charged less—there may be other reasons to charge premiums for travel in these areas and during these times that I have not explored. My cost allocation study (Mallett, 2022) does not account for externalities, including the costs of congestion beyond production costs of serving it. Core areas of these networks and peak times of travel may generate so much crowding and inconvenience costs for passengers—for example, BART passengers departing downtown San Francisco during the evening commute often backtrack to secure a seat—that a premium may be warranted for use in these areas or during these times to internalize delay time costs or manage demand. Additionally, minimum fares or trip length restrictions are often used to manage capacity or to product differentiate transit services. For example, BART's minimum fare assumes a trip of at least six miles to distinguish its regional focus from the local focus of peer agencies. Similarly, New York's Metro-North Railroad does not sell fares for travel between Harlem/125th Street and Grand Central Terminal stations to emphasize its commuter rail orientation, differentiating it from New York City Transit's local travel focus. In this analysis, I do not control for these policies or objectives, which can inflate the cost recovery level found for peak-period travel and travel in core areas of each network.

As with most fare equity studies, I do not test how demand would respond to a fare structure or service change that corrects for the inequities found, nor do I incorporate aggregate economies in my analysis. It is conceivable that changing fares or service output patterns to achieve cost recovery equity would simply redistribute travel patterns, creating new patterns of inequities, rather than eliminating them. Furthermore, core segments of networks benefit from ridership associated with both core-centric and less core-centric travel; riders who travel within the core "overpay" partly because they are sharing links and stations with riders who "underpay." At the same time, it is possible that the costs of maintaining service in outlying areas outweighs the assumed scale and network benefits it delivers, and that more intensive operations in the core area would be more allocative efficient. Regardless, I do not control for network economies. Finally, I focus principally on allocative efficiency implications (i.e., when and where transit is produced) and do not consider production efficiency (i.e., how much service output minimizes average costs). Thus, it is possible that recalibrating service output to correct cost recovery disparities could come at the expense of increased per unit costs of production—or it could reduce average production costs. To-date, models that can control for both allocative and production economic factors are underdeveloped (Basso et al., 2011; Mallett, 2024).

Other broad and societal considerations—impacts on travel mode cross-elasticities, implications on access equity, and implications on environmental mitigation goals of transit, to name a few—generally treat travel and location decisions as exogenous to the transportation system. That is, they accept travel demand as fixed and attempt to influence modal outcomes and access disparities given this. One of my goals with this research is to challenge this assumption. Travel and location choice are a bundled decision, and transport subsidies inform these decisions (e.g., Alonso, 1964; Mills, 1967; Muth, 1969). Hence, internalizing transport costs may lead to changes in location and travel decisions (Brueckner, 2005). Analyzing how fare or service changes interplay with these many considerations is well beyond the scope of one study but worthy of future research.

Nonetheless, I contribute to this broader, interdisciplinary question by laying a foundation for understanding how subsidies and allocative inefficiencies are distributed across two rail networks. Future case studies can help expand the generalizability within and across regions and modes of transport.

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Appendices

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