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Spatial and Temporal Variability of Rail Transit Costs and Cost Effectiveness

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Abstract

Previous research has evaluated the temporal variability of transit costs and shown that peak period service costs more to operate in both gross and net terms. However, research on spatial variability of transit costs, particulalry for modes other than bus transit, is quite limited. Using transit agency data on labor and train allocations in the United States, I develop an accounting cost model that allocates variable and semi-fixed capital costs to times of day and each link and station of two regional rapid rail transit networks—the San Francisco Bay Area Rapid Transit District (BART) and the Metropolitan Atlanta Rapid Transit Authority (MARTA)—to evaluate temporal and spatial variability of costs and average costs per rider. I find that costs per hour are highest, but average costs per rider are lowest, during weekday peak periods in both systems, and that costs are highest and costs per rider are lowest in the urban core area of the BART system, while there is no clear spatial pattern in the MARTA system.

Keywords

policy and organization, executive management issues, economics, revenue, finance, cost models, transportation equity, public transportation, heavy rail, management, operation, urban, rail, passenger rail transportation

Public transit agencies in the United States regularly monitor costs, cost recoveries through fares (farebox recovery ratio), and various factors of production. These data are internally used for such things as operating and capital planning, as well as externally reported to local, state, and federal agencies for such things as determining funding allocations. However, much of the reporting of these data to higher levels of government is done at a system-wide level that does not account for location or temporal variability in costs. As a result, higher levels of government are not able to regulate how efficiently subsidies are being used across space and time in the networks—for example, ensuring money is not over-allocated to a very low ridership area of a network when a more efficient use can be achieved by allocating resources to a high ridership area. And although some transit operators use these data to account for spatial and temporal variability in costs and performance for service and capital planning purposes, the cost models used tend to be underspecfied and exclude both fixed and semi-fixed asset costs, leading to their estimations of spatial and temporal variations being incomplete (e.g., Taylor, et al. (*1*)). Among other examples, the cost of providing peak service is often underestimated, the cost of providing off-peak service is often overestimated, and the cost of providing more capital-intensive modes of transit is often underestimated in transit agency cost models (e.g., Taylor et al. (*1*)). So, while better than the aggregate data reported to higher levels of government, transit operators' monitororing of the occassions of costs still limit how informed their operating, fare policy, or capital investment decisions that account for location and temporal variabilities can be.

Similarly, while state and federal governments' ratings of transit capital projects have increasingly incorporated an applicant's ability to finance operations of the project once built, this assessment is based on the resulting systemwide operating costs; spatial and temporal variabilities in operating costs are not evaluated. Thus, even

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though the construction of a new rail line may lead to cost-effective operations (i.e., a low average cost-per-trip) in one area and cost-ineffective operations (i.e., a high average cost-per-trip) in another, the entire project may be eligible for funding based on an aggregate assessment.

While much research has evaluated the temporal variability of transit service costs, it has focused principally on bus transit, has relied on far less granular data than is available today, and typically only compares peak service to off-peak service despite transit operators having many service time periods. Surprisingly, almost no research has been done on the spatial variability of transit costs. Of what has been done, only bus transit has been studied, and the analyses highlight route-by-route variability (e.g., Cherwony and Mundle (*2*)) or urban-suburban variability by either aggregating to bus yards (e.g., Cervero (*3*)) or city boundaries (e.g., Hodge (*4*), Iseki (*5*)) and labeling all route-miles associated therewith as urban or suburban. In addition, the time and location variability of outcomes, or cost-effectiveness, is not considered in much prior research. While providing service at a particular time or in a particular location may cost more, it may deliver more in the form of ridership, so be more cost-effective.

In this research, I develop an accounting cost model to evaluate the spatial and temporal variability of rail transit costs and cost effectiveness measured using average cost per rider. My objective is to evaluate whether there is a temporal or spatial pattern of the incidence of transport costs in both total and per-rider terms. Based on past research findings, I hypothesize that there is, and that both the total and per-rider costs are highest during the peak period and in outlying areas of the networks. Two rail transit operators with similar operating characteristics—the San Francisco Bay Area Rapid Transit District (BART) and the Metropolitan Atlanta Rapid Transit Authority (MARTA)—are used as case studies. Fiscal Year 2019 (FY19)—July 1, 2018, to June 30, 2019—is used as the study period to mitigate the impacts of the COVID-19 pandemic in the analysis.

I intend to use findings from this research in subsequent research to evaluate whether farebox recovery is temporally and spatially variable such that different times and locations of service receive more subsidies than others, and whether there is an optimal pricing structure that equalizes cost recovery across the network.

Accounting Cost Models in Transit

Cost models relate an entity's total costs to a set of cost inputs. Equation 1 offers a simplified cost function, derived from (Pels and Rietveld (*6*)), wherein the cost of the entity is the sum of a fixed cost and the product of a variable cost and the number of variable inputs.

$$C = a + by \tag{1}$$

where
$C =$ the total or per-output cost,
$a =$ a fixed cost,
$b =$ a variable cost, and
$y =$ the number of units produced subject to b costs.

To measure service output costs of production (i.e., elements of expenditure) for an entity, accounting cost models (e.g., Pels and Rietveld (*6*))—sometimes called cost allocation models (e.g., Berechman (*7*)) or "activity-based" cost models (e.g., Basso et al. (*8*))—are used to relate servie outputs to a series of input costs, as reflected in Equation 2. That is, they measure the occasions of outputs for an entity by associasting them with the costs of inputs (i.e., base level costs incurred in production). Some common input-output relationships in transit industry accounting cost models include the relationship between the output of vehicle-miles and the inputs of fuel and vehicle maintenance, and between the output of vehicle-hours and the input of vehicle operators (labor). As is evident, Equation 2 effectively subdivides Equation 1; the summation of costs of all outputs, i, will equal total costs.

$$C_i = a_i + \sum_{j=1}^{n} b_i y_i \tag{2}$$

where
$C_i =$ a cost of output, i.
$a_i =$ a fixed cost allocated to output, i
$b_j =$ per-unit costs of cost output, j, allocated to output, i
$y_j =$ the number of units of cost input, j, used

To measure variability across some dimension, such as time or space, an accounting cost model can be further subdivided by addinding dimensional subscripts to Equation 2. This would be done if, for example, a transit operator wants to understand how its total costs or specific output costs (e.g., vehicle-miles) vary by different production activities across times of day (e.g., morning commute, midday, late evening, etc.). In this example, the cost of vehicle-miles during a particular time period would equal a fixed cost assigned thereto plus the sum-product of the volume of each allocated cost input used during the time period and their per-unit cost. Adding dimensions to the model can support a transit operator's evaluation of where different investments can reduce costs, such as substituting between the size of buses and the frequency of buses in serving peak period travel, and whether there are disproportionate allocations of resources to a particular time period or location relative to fare revenue or demand (i.e., ridership).

Each of the above equations are generalized examples. Among variations, some analytical inquiries may not include a fixed cost, such as if the analysis employs a long-run cost model and sunk costs are the predominate fixed cost in the case being studied–which, by definition, are not included in long-run cost models (Wang and Yang (*9*)).

In research, accounting cost models are useful for descriptive or case studies, as done here, because they can allow an evaluation of when, where, or how money is spent. They are useful in practice for similar reasons and are the overwhelmingly preferred cost model used in practice (Pels and Rietveld (*6*); Basso (*8*)). On the other hand, this approach is substandard from an econometric perspective because, by merely using judgment to associate input costs with different outputs, it lacks theoretical foundation and does not account for the interrelationship between cost inputs to estimate per-unit costs of production (*8*). For example, the number of operator-hours generated is clearly conditional on the number of railcars or buses in the inventory for operation, but such cosntraints are ignored in accounting cost models. To account for the interrelationship of costs, statistical cost models that relate production output costs to various inputs and the interrelationship between them are more appropriate.

In addition, as alluded to in the introduction, many–but not all–transit agencies' accounting cost models are aggregate in nature; they lack dimensional variability. In these instances, temporal, spatial, and other cost variability is not monitored or used in making resource allocation decisions. Instead, many transit operators, through either administrative choice or policy directive, supply transit service either in a coverage-based format that emphasizes equal or minimal levels of service across the network, or a performance-based format that is more demand-focused but not necessarily considerate of cost or cost recovery patterns (*10*). As well, transit operators generally do not account for capital assets in their accounting cost models, leading to service times or locations that are capital-intensive but not labor-intensive having deflated cost estimates, or vice-versa for services that are labor-intensive but not capital-intensive (Taylor et al. (*1*)).

Accounting for Capital Costs

Capital assets are assets that have a life greater than the timeframe covered by the accounting cost model–typically one year (Walker and Kumaranayake (*11*), referencing Creese and Parker (*12*)). In transportation, many fixed capital assets, such as physical infrastructure, are arguably sunk costs because they are "irrevocably committed and cannot be recovered" (Wang and Yang (*9*)). Once land is bought and tunnels, bridges, and tracks constructed, these investments are a sunk cost of doing business; they cannot be recovered if operation of them is to continue. So, while these assets may require maintenance or rehabilitation, I contend that the original capital, by definition, are not a long-run cost because, ex-post construction, it is an investment that cannot be recovered. By comparison, semi-fixed capital assets last longer than one year, so are a "capital asset" (Walker and Kumaranayake (*11*)), but unlike fixed capital assets, there are variable aspects to the use of semi-fixed capital assets. Vehicles, computers, and heavy maintenance equipment–all whose use and scale vary by service output patterns-are examples of semi-fixed assets in the transit industry.

How capital assets are accounted for in an accounting cost model depends on the objective of the model. Because capital assets last longer than the study period, a researcher or analyst must determine how to charge capital assets to the study year even if they were purchased in a different year or last into later years. Walker and Kumaranayake (Walker and Kumaranayake (*11*)) survey five common reasons for measuring annual capital asset costs, including for budgeting, project efficiency and sustainability review, project expansion, project replication, and economic evaluation (*11*). If the objective is to conduct a benefit-cost analysis, it is important to account for the opportunity cost of the investment. In this case, estimating the cost of the asset in study-year dollars and dividing by its life expectancy is appropriate, as this allows for a side-by-side comparison of options. Furthermore, to account for the lost opportunity to earn interest on the money and use it for a future investment (i.e., the time value of money), applying a discount rate is appropriate in this type of model. Conversely, if the goal is merely to account for realized expenditure and charge it to the study period, a straight-line depreciation based on the original purchase price and life expectancy of the asset is appropriate for annualizing assets' costs and charging them to the respective year(s) of the study.

Finally, not all capital assets are necessarily relevant for a model. If the goal is to internally compare total or marginal costs across some dimensional variation, such as time periods of service, only assets whose use or allocations vary across that dimension are particularly relevant. These are *partially allocated cost models* (Cherwony et al., (*1, 13*)). By comparison, *fully allocated cost models* allocate all capital assets and are useful for comparing the costs of two or more systems or options, such as when conducting an alternatives analysis before making a major investment (Cherwony et al., (*1, 13*)).

In this research, I develop a partially allocated cost model that accounts for assets whose scale varies by time and location of service, and apply the budgetary approach for annualizing asset costs. This supports my objective of analyzing the spatial and temporal incidence of long-run rail transit operating costs–that is, the

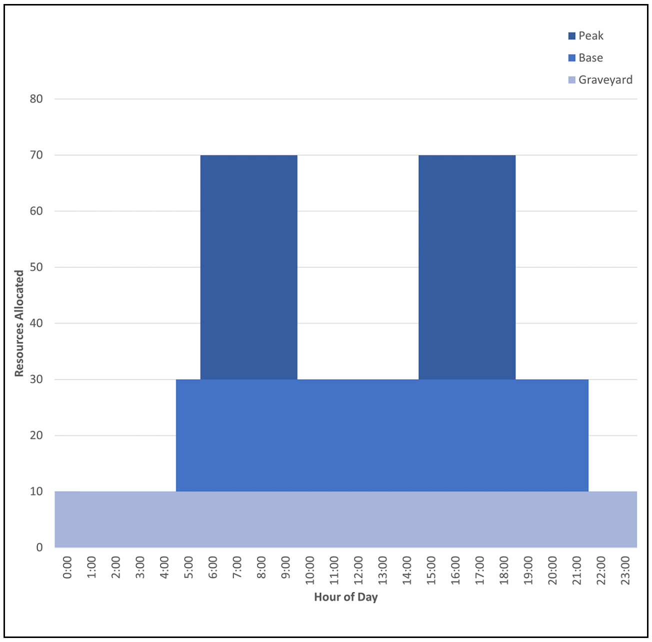

Figure 1. Marginal cost approach to allocating resources by time period.

ex-post construction costs of operating the rail network–in both gross and per-rider terms.

Literature Review

Transit cost model research includes both social science research and transport economics research. The former aims to estimate the efficiency or equity implications of transit services as they are operated. These types of studies tend to rely on accounting cost models that allow costs to be assigned to different times or locations of service so that the incidence of costs or subsidies of the system as built and operated can be evaluated. By comparison, transport economic cost model research aims to identify optimal operating supply that achieves some economic objective, such as welfare or profit maximization. For these types of analyses, statistical models are ideal.

Research on the efficiency and equity incidence of transportation operations was popular in the late 1970s and the 1980s, but has had limited empirical contribution since. Apart from being outdated, the research has almost exclusively focused on bus transit and temporal variability. Rail transit and spatial variability are not well-represented in social science-focused transit cost allocation research to-date, largely because of historically insufficient data granularity. Furthermore, much of the research evaluates *cost* (i.e., the amount spent) variability, despite *cost effectiveness* (i.e., the amount spent per unit of benefit) being more important for program evaluation.

Early research involved methodology development. (Cherwony et al., (*13*)) provide a comprehensive overview of various transit costing procedures, includiong various "methods" and associated "approaches." The suggest that accounting cost models that use one variable (what they call "average cost models") are inviable because they are too insensitive to marginal costs and dimensional cost variability to reasonably evaluate the costs of service changes or occasions of costs, respectively. Among more ideal models are multi-variant account cost models (what they call "fixed/variable cost allocation models") because they are simple to implement and more accurately measure occasions of costs than their single-variable counterpart. However, these models still inherently rely on average costs, so are not ideal for measuring marginal costs or the costs of service changes. Finally, statistical approach (cost) models have the opposite pros and cons; they are ideal for measuring marginal costs and th ecosts of service changes but are not as simple to set up nor ideal for estimating the occasions of costs.

How capital assets are to be allocated to different time periods was subject to much debate as well. Some argue that, since services would likely not be built and operated but for peak demand, the peak period should be charged fully for capital costs (e.g., (*14*, *15*)). Others suggest this arbitrarily charges common or "lumpy" costs to a single group of users, thereby overlooking the common cost nature of these investments and the variability to which the resources are used by different time periods of travelers (e.g., *16–18*). Parody et al. reference various studies in utility pricing (e.g., Coase) in furtherance of this (*19*, *20*).

The answer to this debate for some empirical studies was to take a "middle ground" by allocating an 85% share of capital costs to the peak and 15% to the base (*3, 19, 21*). A more robust approach was developed for the Bradford Bus Study and applied by Cervero for labor costs and Taylor et al. for transit vehicle costs (*1, 3, 22*). The method identifies marginal costs based on the share of units used during a particular time period. To be sure, this is not the traditional economic marginal cost of producing one more trip or one more seat-mile, but the lumpy marginal investment cost of serving a particular time period. Thus, assets used solely during the peak period are fully charged to the peak period, while those used across multiple time periods will have their costs shared amongst those time periods. Figure 1 illustrates this marginal cost approach. If the resources in Figure 1 are railcars, 40 are only used 8 h of the day for the peak period; 20 of them for 16 h of the day; and 10 of them for 24 h of the day. In this case, the peak period is solely responsible for the cost of 40 railcars, half the cost of 20 railcars, and one-third the cost of 10 railcars.

Although allocating transit vehicle costs based on some variant of vehicle-hours or capacity allocations is the going standard, Kerin theoretically showed that if vehicle-miles were used for allocating transit vehicle costs, the off-peak can be more costly to serve than the peak (*23*). Specifically, if a longer time period demands fewer vehicles but generates far more vehicle-miles during the length of the time period compared with the peak period, then the wear-and-tear costs of this time period's mileage-intensity can outpace the costs of the peak period's capital-intensity. Again, industry practice today, including the federally defined life of transit vehicles, is to base vehicle costs on units of time. Even so, as is evident by the average retirement age of buses being three years later than their standardized life expectancy (Laver et al., (*24*)), and many vehicle warranties having both a time-life and mileage-life element to them, there is a basis for evaluating life and allocating costs of vehicles by their miles of use.

The research broadly shows that there are high marginal costs for providing peak period service (*19, 21, 25, 26*)). Although Vickrey theoretically showed that congestion pricing was warranted for the New York City Subway system because of peak-to-base cost and externality differences, Parody et al. are credited for being the first to empirically estimate the time-variant cost recovery for rail transit (*19*, *27*). They used 1983 cost and ridership data submitted to the Urban Mass Transit Administration by all transit operators, allocated operating costs based on revenue-miles, and allocated capital costs based on the aforementioned 85/15 peak-to-base share. They found that it costs 45% more (net) per trip to serve peak period travel overall; for bus, subway, and commuter rail, independently, these numbers are 27%, 27%, and 41%, respectively. This research is also among few that measures cost effectiveness (i.e., the average cost per rider). Cervero evaluated the equity of fares using a revenue-to-cost ratio factored by miles and found that the peak period has a lower cost recovery per mile amongst its users (*3*). But, like Parody et al., he focused only on base versus peak service and allocated capital costs using an arbitrary 85/15 peak-to-base ratio (*19*). His allocation of labor, however, followed Cherwony and Mundle by factoring peak costs using a relative productivity ratio (*25*). Some studies from this era suggest that peak service subsidizes off-peak service because the revenue generated by peak travel offsets the additional costs of serving it (*28*). However, studies in this latter group generally ignore the capital costs of serving peak travel.

Among more recent studies are Taylor et al., and Ripplinger and Bitzan (*1*, *29*). Taylor et al. run parallel partially allocated and fully allocated cost models for the Los Angeles Metropolitan Transportation Authority's transit system and contrast it against the agency's cost model (*1*). They find that peak period service costs much more than base service on both a marginal and total basis, and that the agency's model, which does not include any asset costs, underestimates peak bus service costs by 36%, overestimates base bus service by 17%, and underestimates the cost of light rail service relative to bus service by 266% because of not distinguishing between them. However, Taylor et al. do not evaluate cost effectiveness (i.e., cost per rider) or spatial variability (Taylor et al. (*1*)). Ripplinger and Bitzan devise a transcendental-log cost function to evaluate the economies of scale and monopolistic opportunities of small transit operators (*29*). While their research does not contribute to the questions of spatial or temporal cost variability, they find that the provision of service by multiple providers in a single area creates a Hotelling effect and is a basis for natural monopoly—implying there is such thing as too much service relative to demand in an area.

Finally, transport economics literature broadly shows that some areas of a transport network may inevitably be more subsidized than others, depending on the objective of the operator—for example, cost minimization, profit maximization, or welfare maximization (e.g., Hörcher and Graham (*30*), and Chang and Schonfeld) (*31*). As multioutput firms, transit agencies serve multiple different origin-destination pairs of trips, each a unique output, and all consumers depend collectively on each other to share in the costs of travel. However, these studies assume that a network is fixed and evaluate optimal operations based thereupon, so do not foster an assessment of whether particular segments of a network are wasteful or particularly high-performing. It is possible that a poor performing segment of a network makes it not viable for further operation (or construction to begin with), and this cannot be assessed if it is assumed a network is fixed. Other transport economics literature explores the economies of scale, economies of scope, or economies of density of transport networks (e.g., Basso and Jara-Díaz (*32*)). These studies also focus on fixed networks and are more theoretical than applied.

Missing from the above review is spatial variability in costs. At best, Cervero indirectly evaluates this using "cost centers" or yard facilities to evaluate how cost patterns vary by the areas serviced by each yard (*3*). He finds that yards with routes that cater to peak travelers and longer-distance travelers—both of whom are more concentrated in suburban areas—cost more and recover less. Otherwise, the literature on spatial cost variability emphasizes variation in tax-base recovery. Hodge allocated operating costs to urban and suburban Seattle,

Table 1. San Francisco Bay Area Rapid Transit District (BART) and Metropolitan Atlanta Rapid Transit Authority (MARTA) Reported Operating Data

	BART	MARTA
Miles (mainline)	109.4 mi	48 mi
Stations	48 stations	38 stations
Schedule structure	Fixed headway	Fixed headway
Fare structure	Distance-based	Flat-rate
Farebox recovery ratio (reported)	72.2%	37.4%
Vehicle revenue-miles	77,986,155 mi	22,511,413 mi
Annual trips	125,105,460 trips	65,217,325 trips
Annual passenger-miles	1,756,364,558 passenger-miles	450,023,139 passenger-miles

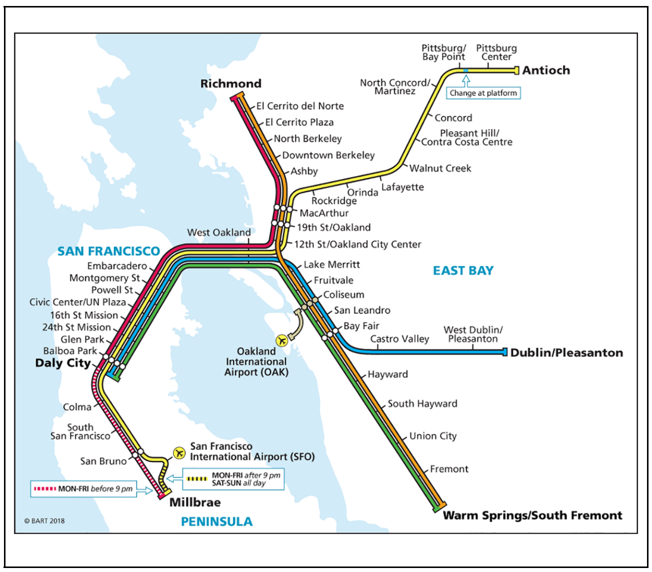

Figure 2. San Francisco Bay Area Rapid Transit District (BART) system map effective July 1, 2018, to February 10, 2019.

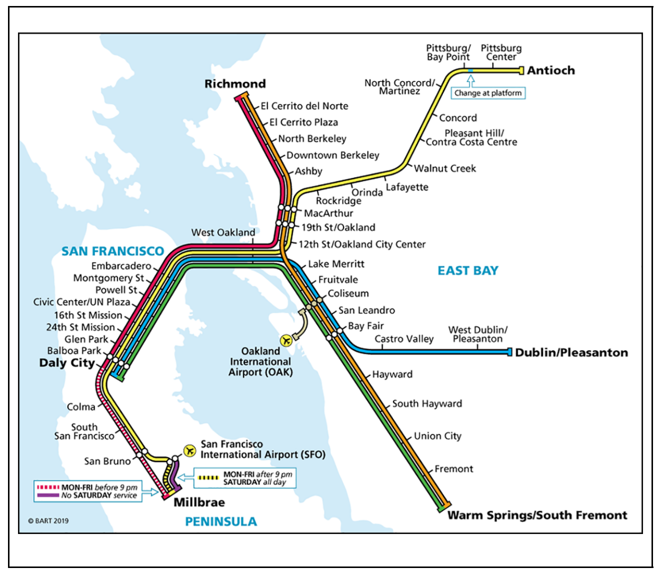

Figure 3. San Francisco Bay Area Rapid Transit District (BART) weekday/Saturday system map effective February 11, 2019, to June 30, 2019.

Washington, using vehicle-miles and vehicle-hours as cost outputs, and evaluated the extent to which these costs are recovered through fares and the tax base in urban and suburban areas (*4*). Iseki used a more robust cost allocation model to conduct similar analysis in Toledo, Ohio (*5*). They both find that the urban area has higher transit patronage and farebox recovery, but that net subsidies when the tax base is accounted for go from suburban areas to urban areas. Still, these studies rely on highly aggregate geographic units, focus on bus transit, and emphasize tax reliance variation as opposed to spatial and temporal cost effectiveness variation.

Fully missing from the aforementioned analysis is anything that looks specifically at rail cost effectiveness. Parody et al. evaluate rail cost recovery, but do so at a national level and focus only on peak-to-base variability using allocation methods that today are primitive (*19*). And while Taylor et al. built a more robust model to assess the time-variant costs of light rail in Los Angeles, California, they conduct no cost effectiveness evaluation of the service (*1*).

Data and Methods

My objective in this research is to evaluate the long-run spatial and temporal variability of rail transit service costs and cost effectiveness (measured by average cost per rider). To do this, I devise a partially allocated, accounting cost model for rail transit that excludes fixed capital assets, but includes variable costs and high-cost semi-fixed assets whose use or inventory vary by time and location. Several other costs-pollution externalities, congestion (crowding) externalities, value of land, and parking facilities, to name a few-are also excluded because of these being independent of railroad operating

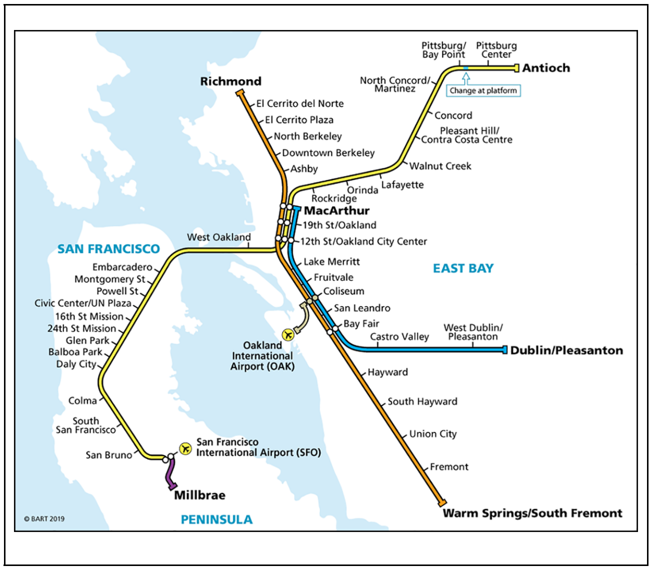

Figure 4. San Francisco Bay Area Rapid Transit District (BART) Sunday system map effective February 11, 2019, to June 30, 2019.

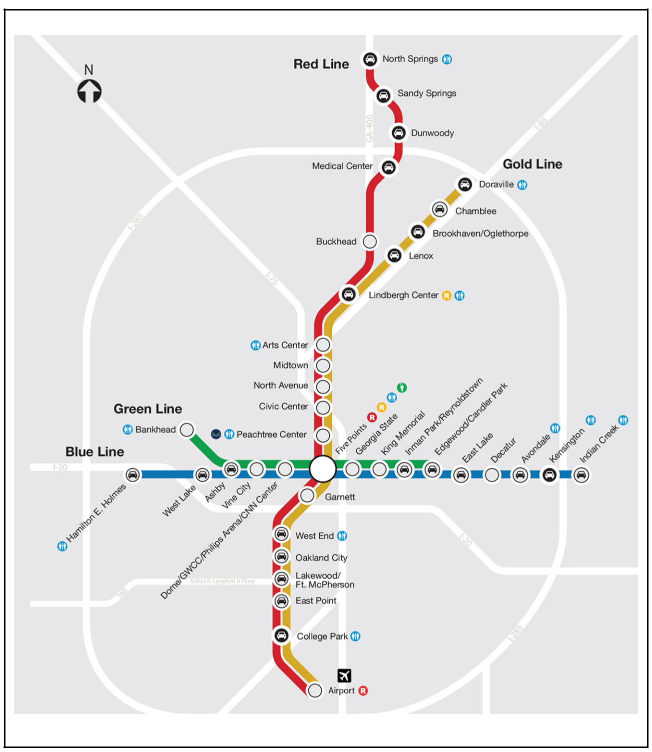

Figure 5. Metropolitan Atlanta Rapid Transit Authority (MARTA) system map effective in fiscal year 2019.

costs. I provide an outline of various types of costs and why they are or are not included in the analysis as an article supplement. By using an accounting-based model and only including long-run costs (i.e., exclusive of the sunk costs of construction, etc.) that are spatially and temporally variable, I can better analyze when and where ongoing costs are occasioned relative to demand in ways that cannot be done with a statistical cost model. To be sure, this does not measure the total cost of rail investments and cumulative spatial and temporal incidence of costs; that would require a fully allocated cost model, inclusive of all fixed costs. Rather, by limiting what I include in the following model, I measure the location- and time-variability of operating costs of the rail networks, as built and operated. This is useful for understanding the long-run, recurring cost impacts of the investment.

Case Selection

To generalize the findings and support subsequent research on how efficiency and fare equity varies by fare structure, I use two regional rapid rail transit operators with different fare structures—BART and MARTA—as case studies. Both agencies' mainline rail systems functionally link sparsely spaced suburban stations to an urban core set of stations and operate using rapid rail technology and relatively fixed headway schedules, and provide few, if any, skip-stop services. This is functionally distinct from commuter rail systems that generally terminate at a single "union station" in the urban core, have variable schedules, and offer skip-stop runs; as well as traditional rapid rail transit systems that are urban-focused with frequent stops and no-to-little emphasis on linking suburban areas to an urban core. In addition, regional rapid rail transit operators are the only rail operators with highly granular ridership data because of riders having to tap on and off the systems, making them ideal for this analysis.

BART and MARTA System Information. Table 1 shows summary operating information of the BART and MARTA mainline rail systems, based principally on the agencies report in their National Transit Database (NTD) 2019 agency profile.

Figure 2 shows BART's system map effective July 1, 2018, through February 10, 2019. Figures 3 and 4 show the weekday/Saturday and Sunday/holiday system maps, respectively, effective February 11, 2019, through June 30, 2019. During FY19, BART's mainline rail system consisted of 109.4 mi of track and 45 stations. The agency has three "full-time" routes that operate fixed headways on weekdays, Saturdays, and Sundays from opening to closing. One of these routes, the Pittsburg/Bay Point to San Francisco Airport line, has increased peak period headway that is provided with part-time labor. Two "part-time" routes operate from opening through the late shoulder of the evening commute on weekdays and during the midday on Saturdays. With the exception of the

Table 2. Costs, Classifications, and Cost Input Metrics

Cost	Classification	Service output metric	
		Temporal	Spatial
Station agents	Station	Worker-hours	
Station cleaners	Station		
AFC assets	Station	Railcar-miles	AFC assets per station
AFC technicians	Station		
VT assets	Station		VT assets per station
Elevator/escalator workers	Station		
Station-classified department	Station		Assets per station
Train operators	Railroad	Train-minutes	
Railcars	Railroad	Marginal allocations	Link runs
Railcar maintenance assets	Railroad	Railcar-miles	
Trackway maintenance assets	Railroad		
Traction power	Railroad		
Railroad-classified department	Railroad		
Administrative personnel		Proportional to other costs	

Note: VT = vertical transportation; AFC = Automated Fare Collection.

aforementioned supplemental service, the agency scales capacity by resizing its trains rather than changing frequency. During the latter half of the fiscal year, BART adjusted some operating patterns. Most notably, the Dublin/Pleasanton to Daly City line was diverted to terminate at MacArthur instead of Daly City on Sundays, and weekday operations began at 5 a.m. instead of 4 a.m. The agency also operates a cable-drawn automated guideway and diesel multiple unit (DMU) spur line—the costs of which I exclude to ensure a consistent analysis.

Figure 5 shows MARTA's rail system map. The system consists of four routes—two along a north-south corridor and two along an east-west corridor. The Blue and Gold Lines operate their full length from opening to closing, while the Green and Red Lines are reduced during evening hours to only operating shuttle service between their spur termini and the first station on their mainline. Service capacity is scaled by increasing or reducing the number of trains in-service; MARTA does not resize its trains to serve different levels of demand. In addition, whereas BART has both lead railcars with an operator cab and middle railcars without an operator cab, leading to variation in railcar capital costs across time periods, all MARTA railcars have an operator cab. MARTA also operates bus and streetcar services, both of which I exclude to ensure consistency in analysis.

Data

To spatially allocate costs, I classify assets, labor, and certain variable costs as either a railroad or station cost. Table 2 defines the assets and labor costs included and how they are labeled. For administrative costs, such as expenditures made within the Office of the General Manager, I first split these between transit modes (excluding demand-response transit) based on each mode's share of revenue-miles reported in the NTD annual profile. So, if an agency operates bus and rail, and 70% of the reported revenue-miles are associated with rail, I allocate 70% of administrative costs to rail. I then classify these costs as station or railroad costs, and allocate them to time periods and links or stations in proportion with other costs assigned to each; they are a "commissioned" expense. This is different from some others who treat administrative costs as a fixed cost on the premise that some fixed amount of management is required to run a system (e.g., Taylor et al. (*1*)). However, I treat this as a variable cost on the basis that administrative size scales with the size of operations. Finally, BART's San Francisco International Airport Station has a unique annual cost of $2 million in lease payments and $800,000 in janitorial service paid to the airport. I allocate these costs solely to the San Francisco International Airport Station.

Most data came from the transit agencies. Each agency provided asset inventory data and, for station assets, the allocation of them by station. The agencies also provided purchase or replacement price and life expectancy of the assets. Also, where available, they provided rehab costs and extended life expectancies from rehab of the included assets. Equation 2 defines how annual costs of assets are derived.

$$AnnualCost_i = \frac{\sum_{i=1}^{n}(OriginalCosts_i + RehabCosts_i)}{\sum_{i=1}^{n}(OriginalLifeExpectancy_i + RehabLifeExpectancy_i)} \quad (3)$$

where
$AnnualCost_i$ = the annualized cost of asset i,
$OriginalCosts_i$ = the purchase price of asset i,
$RehabCosts_i$ = the rehab costs expended on asset i,
$OriginalLifeExpectancy_i$ = the original expected life (in years) of asset i,
$RehabLifeExpectancy_i$ = the expected life extension from rehabilitation of asset i, and
i = a unique asset within an asset group.

Track rail costs are not reflected in any cost data, so are not allocated in this way. Instead, I charge the cost-per-mile of track rail—\$199,267.20, according to Compass International, Inc.'s 2017 Railroad Engineering and Construction Costs Benchmark, inflated to 2019—to each link and each time period based on the number of railcar-weight-miles and passenger-weight-miles generated along the link or during the time period relative to the weight-life of rail (Equation 3). The weight used for a BART railcar is 63,000 lb; MARTA railcar is 81,000 lb; and passengers is 181 lb (*33–35*). A BART engineer indicated that the agency relies on the American Railway Engineering and Maintenance-of-Way Association's (AREMA) standards to make track rail replacement decisions, and that AREMA's documented life expectancy of straight track rail for BART is 360 million gross tons (MGT). This number was not found in a review of the AREMA manual, but is not far astray from some research, including Zhao et al.'s finding that life cycle costs of rail are minimized at a life of around 308 MGT (*36*).

$$Cost_i = \frac{\$199,267.20 \times \{(RailcarWeight \times RailcarMiles_i) + (181 \times PassengerMiles_i)\}}{360\ MGT} \tag{4}$$

where
$Cost_i$ = the annualized cost of link i, or time period i,
$RailcarWeight$ = the weight of a railcar,
$RailcarMiles_i$ = the number of railcar-miles generated along link i, or during time period i, and
$PassengerMiles_i$ = the number of passenger-miles generated along link i, or during time period i.

In addition, the agencies provided end-of-year financial reports of each department's expenditure on human capital and ancillary expenses; bid schedules of train operators, station agents, and station cleaners; wages and fringe rates of select positions; train run schedules, including the train length of each train run; track distance and runtime matrices; and collective bargaining agreements. They also provided the count of riders for all origin-destination trips organized by the derived time periods (BART) or at 15 min intervals for the entire study period (MARTA).

Much literature has shown that the peak period is markedly more expensive to operate due to union work rules that require premium payments for split shifts or other inefficiencies (Chomitz and Lave (*37*); Pickrell (*38*); Wachs (*39*); Winston and Shirley (*40*)). However, while MARTA has a split shift workers, no premium is paid for this. And while BART pays shift differentials, they do not have split shifts to serve the peak period and the shift differentials do not align with the operating time periods I identify in this study. BART also has other workforce inefficiencies, include a low pay-to-platform ratio for their train operators by industry standards, according to agency staff I consulted. As with the shift differentials, these are broadly inefficient work rules that do not correlate with spatial and temporal operating patterns.

Lastly, each agency's 2019 NTD annual profile was collected.

Model—Temporal

To temporally allocate costs, I devise time periods using the marginal allocation method for railcars. Figures 6–10 show the count of trains and railcars in-service for every minute of the day in each system, derived from run schedules. For BART, the period from July 1, 2018, through February 10, 2019, is shown and is not dissimilar to the distribution for the period from February 11, 2019, onward.

I assign a train and its railcars to a time period based on the departure time of the train. So, if 10:00 a.m. is a time period cutoff and a train departs at 9:59 a.m., I assign it to the time period *ending* at 10:00 a.m., even as it may spend most of its time in the adjacent time period.

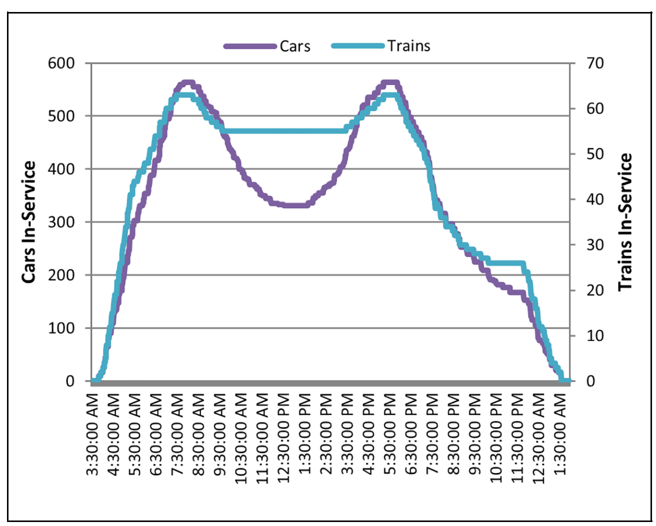

Figure 6. San Francisco Bay Area Rapid Transit District (BART) distribution of cars and trains in-service—weekdays.

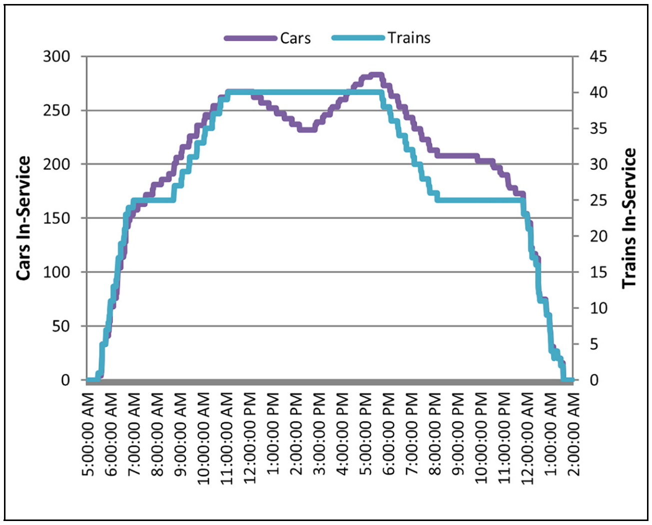

Figure 7. San Francisco Bay Area Rapid Transit District (BART) distribution of cars and trains in-service—Saturdays.

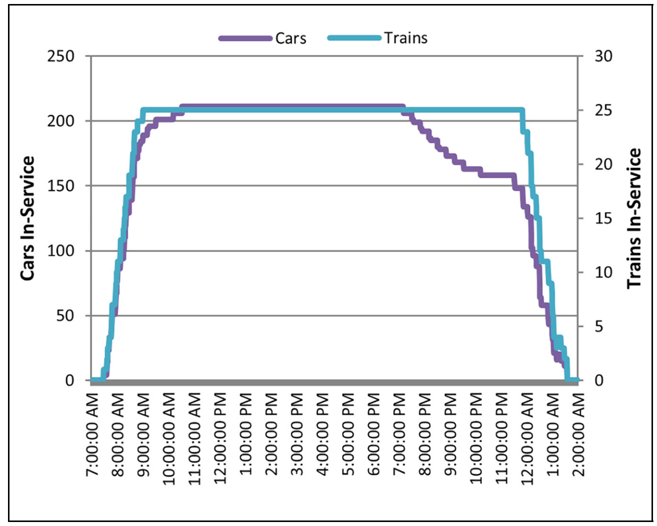

Figure 8. San Francisco Bay Area Rapid Transit District (BART) distribution of cars and trains in-service—Sundays/holidays.

In addition, I assume that any resizing of trains occurs *on arrival* at a terminus.

I then use the cost allocation metrics defined in Table 2 to allocate costs to time periods using Equation 4—the summation across which equals total FY19 costs (Equation 5). Time period costs are proportioned to the number of days operated as a weekday, Saturday, or Sunday/holiday during FY19 and the corresponding total number of annual-hours associated with each time period. To account for BART's change in operating schedule mid-year, I use the weighted average of cost inputs during the two schedule periods to allocate costs.

$$\begin{aligned} Cost_t = {} & \left(\sum_{a=1}^{N} \frac{WorkerHours_{a_t}}{WorkerHours_{aTot}} \times AnnualCost_a\right) \\ & + \left(\frac{RailcarMiles_t}{RailcarMiles_{Tot}} \times \sum_{b=1}^{N} AnnualCost_b\right) + \left(\frac{TrainMinutes_t}{TrainMinutes_{Tot}} \times AnnualCost_c\right) \\ & + \left(\sum_{d=1}^{N} \frac{Minutes_t}{Minutes_d} \times AnnualCost_d\right) \\ & + \frac{\$199,267.20 \times \{(RailcarWeight \times RailcarMiles_t) + (181 \times PassengerMiles_t)\}}{360\ MGT} \\ & + AnnualCost_{f_t} \end{aligned} \tag{5}$$

$$Cost_{Total} = \sum_{t=1}^{N} Cost_t \tag{6}$$

where
$Cost_t$ = the cost of time period t,
$WorkerHours_{at}$ = the number of worker-hours of temporally-allocated classification a, generated during time period t,
$WorkerHours_{aTot}$ = the total number of annual worker-hours generated in temporally allocated classification a,

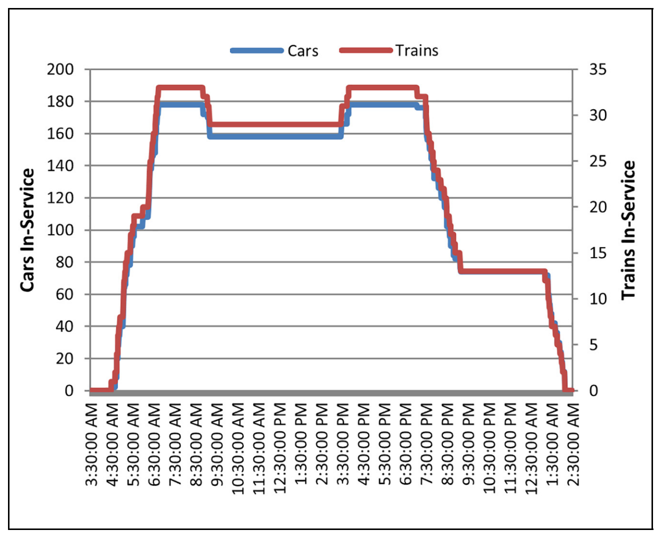

Figure 9. Metropolitan Atlanta Rapid Transit Authority (MARTA) distribution of cars and trains in-service—weekdays.

$AnnualCost_a$ = the total annualized costs expended on worker classification a,
$RailcarMiles_t$ = the number of annual railcar-miles generated during time period t,
$RailcarMiles_{Tot}$ = the total number of annual railcar-miles generated,
$AnnualCost_b$ = the total annualized costs expended on asset b, department b, worker classification b, or traction power that is temporally allocated by railcar-miles,
$TrainMinutes_t$ = the number of train-minutes generated during time period t,
$TrainMinutes_{Tot}$ = the total number of annual train-minutes generated,

$AnnualCost_c$ = the total annualized costs expended on the train operator worker classification,
$Minutes_t$ = the number of annual-minutes associated with time period t,
$Minutes_d$ = the number of annual-minutes asset d is utilized,
$AnnualCost_d$ = the annualized cost of railcar d,
$RailcarWeight$ = the weight of a railcar,
$PassengerMiles_i$ = the number of passenger-miles generated during time period t,
$AnnualCost_{ft}$ = a commission-based administrative cost allocated to time period t,
$Cost_{Total}$ = the total annual costs accounted and expended by the agency,
t = a time period,
a = a worker classification temporally allocated by worker-hours (see Table 2),
b = an asset, department, worker classification, or traction power temporally allocated by railcar-miles (see Table 2), and
d = a railcar or station asset.

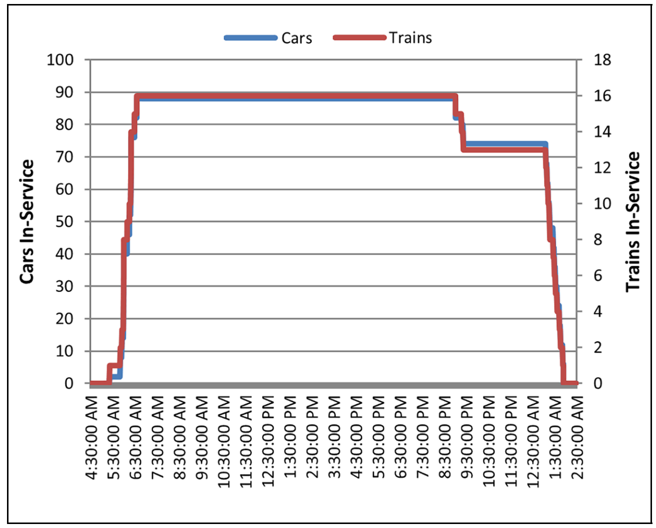

Figure 10. Metropolitan Atlanta Rapid Transit Authority (MARTA) distribution of cars and trains in-service—weekends/holidays.

Model—Spatial

To spatially allocate costs, I allocate costs to links (Equation 6) or stations (Equation 7) based on how they are classified in Table 2. Therefore, two accounting cost models are used, the sum across which will equal the total in expenditures for the year (Equation 8).

$$\begin{aligned}Cost_l = &\left(\frac{TrainMinutes_l}{TrainMinutes_{Tot}} \times AnnualCost_a\right)\\ &+ \left(\frac{RailcarRuns_l}{RailcarRuns_{Tot}} \times \sum_{b=1}^{N} AnnualCost_b\right)\\ &+ \left(\frac{RailcarMiles_l}{RailcarMiles_{Tot}} \times \sum_{c=1}^{N} AnnualCost_c\right)\\ &+ \frac{\$199,267.20 \times \{(Railcar\ Weight \times RailcarMiles_l) + (181 \times PassengerMiles_l)\}}{360\ MGT}\\ &+ AnnualCost_{d_l}\end{aligned} \tag{7}$$

where
$Cost_l$ = the cost of a link of the railroad,
$TrainMinutes_l$ = the number of annual train-minutes generated on link l,
$TrainMinutes_{Tot}$ = the total number of annual train-minutes generated,
$AnnualCost_a$ = the total annualized costs expended on the train operator worker classification,
$RailcarRuns_l$ = the number of annual railcar runs across link l,
$RailcarRuns_{Tot}$ = the total number of annual railcar runs across all links of the network,
$AnnualCost_b$ = the annualized cost of a railcar b,
$RailcarMiles_l$ = the number of annual railcar-miles generated across link l,
$RailcarMiles_{Tot}$ = the total number of annual railcar-miles generated,
$AnnualCost_c$ = the annualized cost of asset c, department c, worker classification c, or traction power that is spatially allocated by railcar-miles,
$RailcarWeight$ = the weight of a railcar,
$PassengerMiles_l$ = the number of passenger-miles generated along link l,
$AnnualCost_{dl}$ = a commission-based administrative cost spatially allocated to link l,
b = a railcar, and
c = a railroad-classified asset, department, worker classification, or traction power spatially allocated by railcar-miles (see Table 2).

$$\begin{aligned}Cost_s = &\left(\sum_{a=1}^{N} \frac{WorkerHours_{a_s}}{WorkerHours_{aTot}} \times AnnualCost_a\right)\\ &+ \left\{\frac{Count_{bs}}{Count_{bTot}} \times \left(\sum_{b=1}^{N} AnnualCost_b + \sum_{c=1}^{N} AnnualCost_c\right)\right\}\\ &+ AnnualCost_{d_s}\end{aligned} \tag{8}$$

where
$Cost_s$ = the cost of a station,
$WorkerHours_{as}$ = the number of worker-hours of classification a, that is spatially allocated to station s,
$WorkerHours_{aTot}$ = the total number of annual worker-hours of classification a,

$AnnualCost_a$ = the total annualized costs expended on worker classification a,
$Count_{bs}$ = the number of station-based asset b located at station s,
$Count_{bTot}$ = the total number of station-based asset b allocated to stations,
$AnnualCost_b$ = theannualized cost of station-based asset b,
$AnnualCost_c$ = the total annualized costs expended on department c or worker classification c that is spatially allocated by station asset count,
a = a worker classification spatially allocated by worker-hours,
b = a station-classified asset, and
c = a station-classified department or worker classification allocated by asset count.

$$Cost_{Total} = \sum_{l=1}^{N} Cost_l + \sum_{s=1}^{N} Cost_s \quad (9)$$

where
$Cost_{Total}$ = the total annual costs accounted and expended by the agency,
$Cost_l$ = a cost spatially allocated to links of the railroad,
$Cost_s$ = a cost spatially allocated to stations of the railroad,
l = a link of the railroad, and
s = a station.

Findings—Temporal Allocations

Figures 11 and 12 show the service output shares of the different time periods for BART and MARTA, respectively. Unsurprisingly, the peak period generates the highest share of many service outputs for both agencies, and many of the peak period's shares of service outputs are high relative to its share of operating hours. Whereas the peak period accounted for just 25% of BART's and 23% of MARTA's FY19 operating hours, its share of railcar allocations was 57% and 40%, respectively. In contrast, the weekday evening hours for both agencies are marked by service output shares that are low relative to the time periods' share of operating hours. This is partly explained by the agencies not providing 24 h service, leading to these time periods including when the last trains of the day are incrementally going out of service (see Figures 6–10).

As a result and reflected in Figure 13, BART's weekday peak service cost \$316M to operate in FY19—about 1.25 times more than the next most expensive time period, weekday base service. For MARTA, although the peak period generates more service outputs relative to its share of operating hours, the total amount of service outputs generated is about equal to weekday base

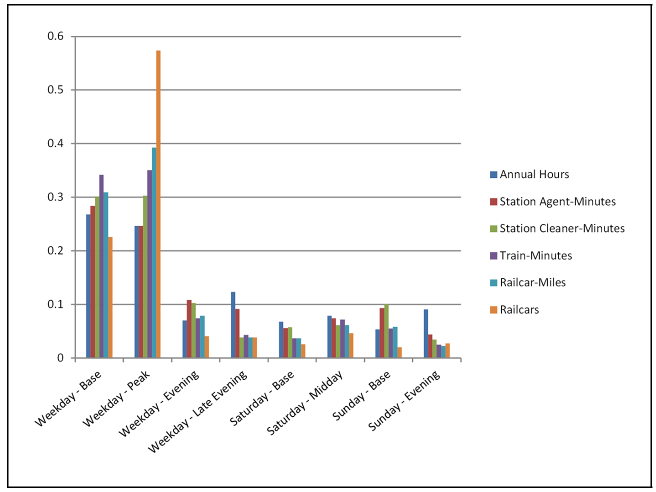

Figure 11. San Francisco Bay Area Rapid Transit District (BART) share of cost outputs by time period.

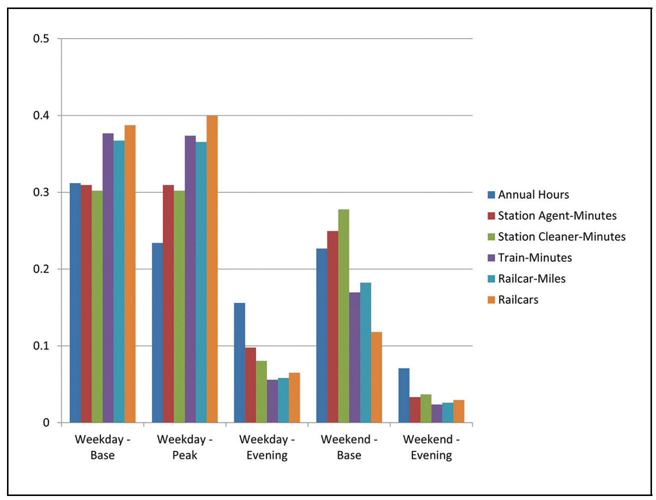

Figure 12. Metropolitan Atlanta Rapid Transit Authority (MARTA) share of cost outputs by time period.

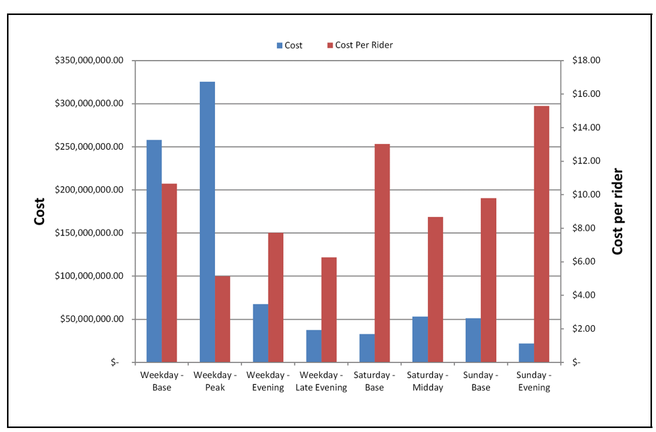

Figure 13. San Francisco Bay Area Rapid Transit District (BART) cost versus cost per rider by time period.

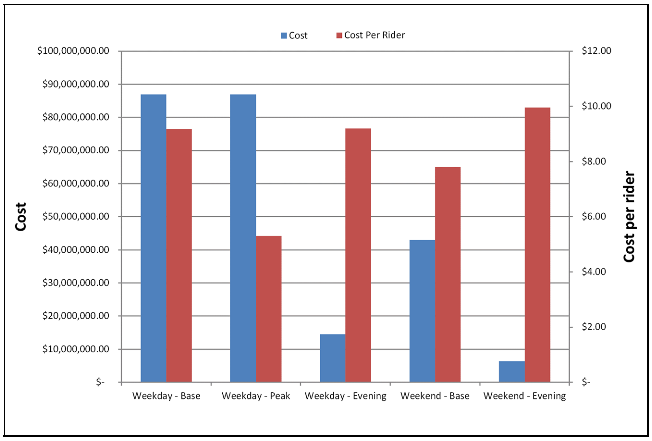

Figure 14. Metropolitan Atlanta Rapid Transit Authority (MARTA) cost versus cost per rider by time period.

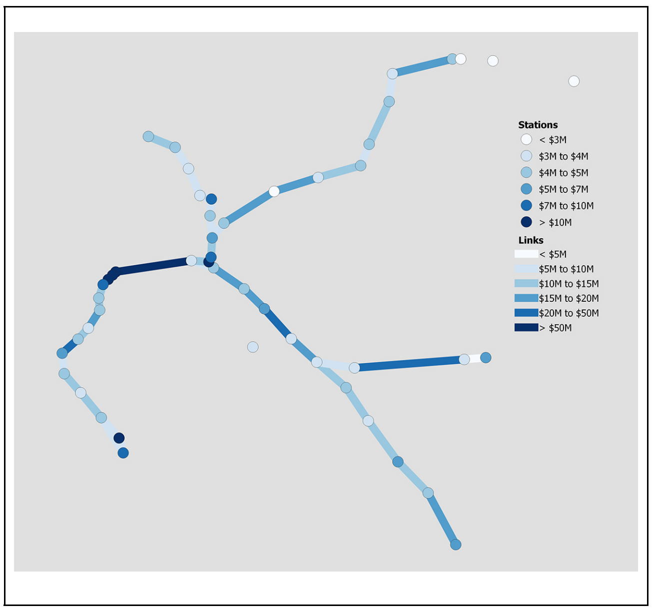

Figure 15. San Francisco Bay Area Rapid Transit District (BART) station and link costs.

service. Consequently, MARTA's weekday base and peak period service each cost around $87M (Figure 14), with weekday base period costing nominally more.

However, when the volume of passengers served during different time periods is considered, the peak period is the most cost-effective operating time period for both agencies. That is, the average cost per unit of benefit, measured as a trip, is lowest during the peak period. Whereas BART's base service cost $10.67 per rider, on average, in FY19, its peak service cost $5.14 per rider, on average. For MARTA, these values are $9.17 and $5.31, respectively. So, while the peak period costs more to operate, it serves so many more trips, thereby reducing the average per-unit cost of a trip.

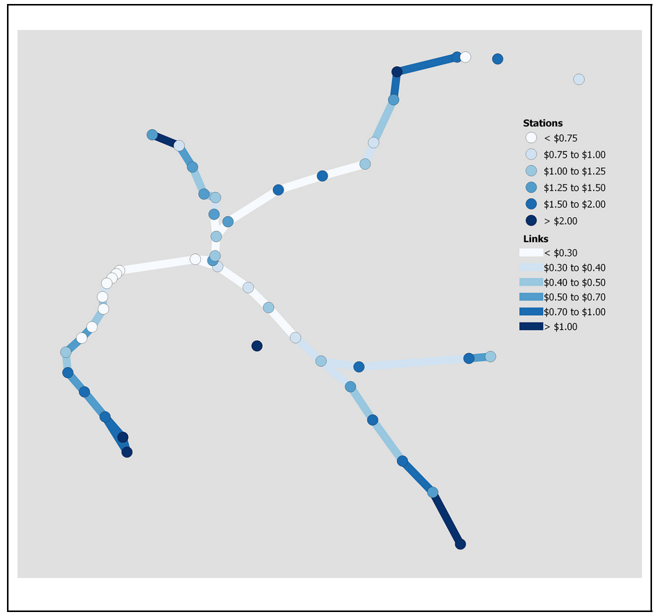

Figure 16. San Francisco Bay Area Rapid Transit District (BART) station costs per rider and link costs-per-passenger-mile.

Findings—Spatial Allocations

As with the temporal findings, when costs are allocated spatially, more expensive links and stations of the BART system tend to also be more cost-effective, and vice-versa. Furthermore, there appears to be a monocentric spatial pattern for both costs and cost effectiveness in the BART system. That is, high-cost, low-average-cost-per-rider stations, and high-cost, low-average-cost-per-passenger-mile links, tend to be concentrated in the core of the system. This is reflected in Figures 15 and 16. At $58M in FY19, BART's most costly link to operate is its Transbay Tube. This is 2.6 times more costly than the next most expensive link of the system. Yet, it is also the most cost-effective link of the system, costing only $ 0.15 per passenger-mile, on average. By comparison, the link between Pittsburg/Bay Point Station and the Pittsburg/Bay Point transfer platform had the lowest FY19 annualized cost of $2.5M but the highest average cost per passenger-mile at $2.34. For stations, BART's two highest cost stations, Montgomery Street and Embarcadero, are also the lowest average cost per rider stations.

However, this spatial pattern does not appear to hold for the MARTA system, as reflected in Figures 17 and 18.

To quantify this monocentric variation, I run ordinary least squares (OLS) regressions for both cost and cost effectiveness, regressing either of these onto track-mile distance from a defined core station—West Oakland station for BART and Five Points station for MARTA. I run this for both links and stations, and define a link's

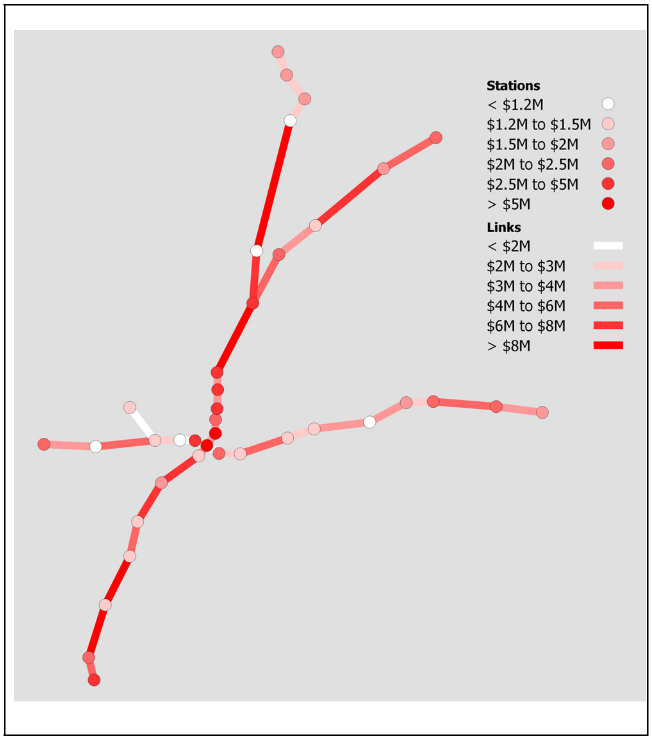

Figure 17. Metropolitan Atlanta Rapid Transit Authority (MARTA) station and link costs.

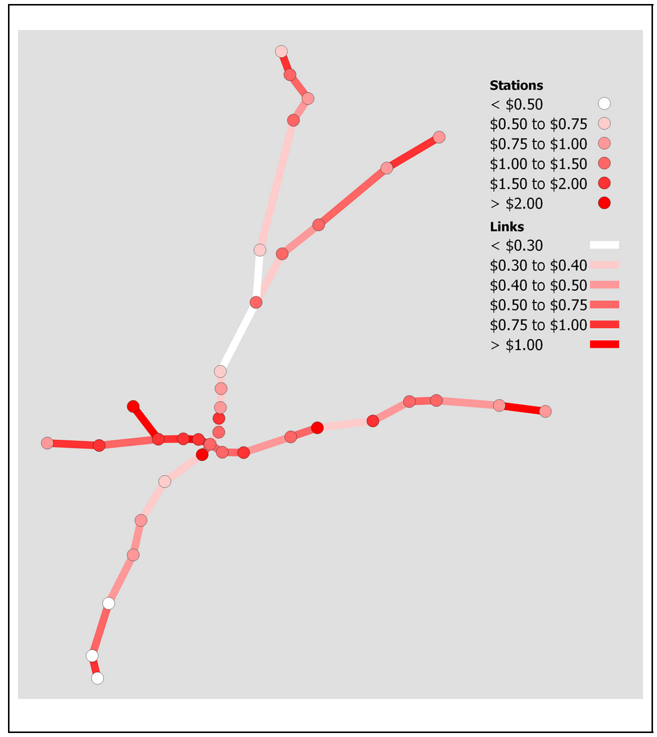

Figure 18. Metropolitan Atlanta Rapid Transit Authority (MARTA) station costs per rider and link costs-per-passenger-mile.

mileage from the core station based on the distance of the station furthest from the core station. Table 3 shows these results. For BART, station costs decrease with distance from the core in a statistically significant way, while both link costs per passenger-mile and station costs per rider increase with distance from the core in a statistically significant way. The model for MARTA's station cost effectiveness suggests that station costs per rider decrease with distance from the core in a statistically significant way.

Discussion and Conclusion

In the preceding analysis, I employed a partially allcocate long-run accounting cost model and have shown that, when variable and semi-fixed capital costs are allocated to times and locations of a rail transit system, a great amount of variability exists. My analysis also underscores that cost and cost effectiveness are distinct evaluation measurements and can lead to opposing conclusions. While core stations and links and peak period service are the most input-intensive and often costliest to operate, they tend to be the most cost effective to operate due to the high density of riders served.

When making an investment decision, both short-run and long-run costs are important to consider. Short-run costs include upfront sunk costs of investment, whereas long-run costs only account for the variable and recurring fixed costs that continue to be incurred into the future (Wang and Yang (*9*)). Once a transit capital project is constructed, the operator will incur a "commitment trap" of having to operate the service (*41*). This research underscores the importance of considering these long-run, commitment trap costs and cost effectiveness of major transit investment projects. Several portions of the BART and MARTA networks have high average per rider annual costs, even when the total annual costs I allocate are low. This suggests that some stations or extensions of these networks may have been a poor capital investment choice from a strictly financial, long-run operations standpoint; they bear a high long-run average cost per unit of benefit.

BART's and MARTA's spatial cost and cost effectiveness outcomes differ. Whereas BART has a monocentric pattern of costs and cost effectiveness, MARTA's spatial cost and cost effectiveness pattern is scattered. One possible explanation of this is that, whereas BART has at least one station agent allocated to every station during all operating hours, MARTA spaces station agent assignments out and their allocations do not necessarily follow ridership patterns. In addition, travel patterns on the BART system are much more monocentric compared to on the MARTA system; whereas two-thirds of all BART trips begin or end at its four Downtown San

Table 3. Cost and Cost Effectiveness Relative to Distance From Core

	Cost				Cost effectiveness			
Agency	BART		MARTA		BART		MARTA	
Links / Stations Variables ↓	Links	Stations	Links	Stations	Links	Stations	Links	Stations
distance_core	−72,213.07	−110,635.3*	118,942.3	−77,139.9	0.0314***	0.0287*	−0.0005	−0.0508**
constant	13,600,000***	6,781,186***	3,589,899***	2,530,831***	0.1141	1.0693***	0.5943***	1.48***
N	47	49	37	38	47	49	37	38
Adjusted R-squared	−0.0712	0.0975	0.0344	0.044	0.3486	0.0851	−0.0285	0.1676

Note: BART = San Francisco Bay Area Rapid Transit District; MARTA = Metropolitan Atlanta Rapid Transit Authority. Statistical significance: ***p ⩽ 0.001, **p ⩽ 0.01, *p ⩽ 0.1.

Francisco stations (8% of stations) that are also the highest ridership stations in the system, the five highest ridership MARTA stations (13% of stations) that account for two-thirds of all trips are not spatially concentrated. Finally, with regard to links, four of BART's five routes converge through San Francisco, resulting in 2.5 min frequency along this portion of the network during commute hours; whereas MARTA's highest combined frequency is one train every 5 min. BART also operates longer trains and carries more passengers, particularly through the core of the system, leading to both greater weight-miles and passenger-miles.

The difference between peak and base cost effectiveness patterns is counter-intuitive to past research findings, but not necessarily inconsistent. Past research suggests that peak period and suburban services are more costly to operate, rely on higher levels of subsides, and are regressively financed (*1, 3, 19, 42, 43*). Yet, this research shows that weekday base and weekend periods are the costliest to operate *on a per-rider basis*. On the one hand, this seeming variance from past findings may be attributable to my not including amortized fixed capital costs-most notably, construction costs-since my analysis is focused on long-run costs. Furthermore, I do not include debt service payments for the purchase of the semi-fixed assets I unclude in my cost allocations. However, I posit that a greater influence of this difference in findings is the fact that BART and MARTA maintain a relatively fixed level of service throughout the day, leading to their peak costs—particularly labor—being less "peaked" than is typical. Increasing midday transit service levels has been a growing point of advocacy, is often promoted as a transport and access equity strategy, and is financially justified based on there being no marginal cost since a train that would otherwise be in storage is put to use. But there is a marginal cost by way of this reducing the peak period's marginal cost of a railcar—never mind the other cost inputs generated. BART's and MARTA's operating patterns show that providing off-peak service levels similar to peak service leads to off-peak periods costing more per rider.

However, peak period and core areas of these systems having a lower cost per rider does not answer whether certain times or locations of service are more heavily subsidized. Even the most cost ineffective times, links, and stations can be the most efficient (i.e., cost recovery) if fare payments cover more of these costs than other times or locations. To evaluate the time and location variability of efficiency and equity (i.e., parity in cost recovery), findings from this research need to be compared with the time- and location-variant fare revenues generated. Future research ought to evaluate this.

This research is not without some limitations. For one, every mile of track is treated the same even though grade, curvature, tangent, and the number of tracks per link will influence wear, maintenance, and rehab costs. Among other examples, the use of a tamper machine is assigned to every grade and mile of track even though this machinery is only used on at-grade track. However, in the absence of structure rehab costs and intervals, which are highest for tunnel and aerial grades of the networks, I generalized the annualized cost of tamper machines. Finally, location and time are not interacted; it is possible that select areas of service are especially costly or cost ineffective during select times and not so during other times. Future research might expand this analysis to interact time and location, as well as incorporate construction and land costs to evaluate their impacts on cost and cost effectiveness patterns.

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Author Contributions

The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

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Supplemental Material

Supplemental material for this article is available online.

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