Fare-Free Transit in the United States: Effects on Ridership, Service, and Finances

Justin Tyndall*

November 7, 2025

Abstract

A growing number of US public transit agencies have eliminated fares as a strategy to boost ridership, expand mobility and achieve transportation equity goals. This study identifies 14 US transit agencies that have recently eliminated fares. A staggered difference-in-difference analysis shows that fare elimination increased ridership by 55%, on average. I find no evidence that fare-free policies were followed by service cuts. In fact, service level and total system investment tended to increase after fares were removed. Lost fare revenue is typically replaced by external funding sources. A synthetic control analysis estimates agency-specific effects, revealing significant heterogeneity.

Keywords: Transportation; Transit; Free Transit; Synthetic Control Method
JEL classification: R41; R48; H40; H72; I38

*University of Hawai'i Economic Research Organization and Department of Economics, University of Hawai'i at Mānoa, Honolulu, HI, United States. *jtyndall@hawaii.edu*.

1 Introduction

Transit agencies periodically adjust fares, balancing fiscal pressures with accessibility and mobility goals. While completely eliminating fares has been rare in the US, a growing number of mid-sized systems have recently adopted fully fare-free policies. These policies could have broad consequences for urban mobility and affordability. In this paper, I document US transit agencies that have recently eliminated fares, identifying 14 systems. On average, ridership increased by 55% following fare elimination. Agencies tended to expand service and investment despite the loss of revenue. I provide new causal evidence on the effects of fare-free transit.

Eliminating bus fares has a number of attractive properties. First, it is a direct financial benefit to incumbent riders. Bus riders in the US skew significantly lower-income (Schouten et al., 2021), meaning these savings can lower the cost of living and reduce economic inequality. Second, removing fares raises public mobility by incentivizing more trips to take place. Increased mobility expands the opportunities for beneficial economic and social interactions in a city. Third, the elimination of transaction costs can improve service quality. Completing a financial transaction for every person entering a bus can take a significant amount of time, which increases vehicle dwell time, potentially degrading service quality. Fare elimination can enable "all door boarding," where riders can enter buses at rear doors, rather than queuing at the front, reducing dwell time. Fourth, fare elimination removes the financial costs of collecting fares. Fare collection infrastructure is costly to maintain and agencies must pay workers to enforce fare payment. Fifth, lowering transit costs might lead to a reduction in car trips, and associated externalities, if travelers substitute between modes. Prior research provides mixed evidence about the size of this substitution effect (Fearnley, 2013; Albalate et al., 2024; Webster, 2024; Vieira et al., 2025).

The primary drawback of fare elimination is the loss of revenue for public transit agencies. Providing high quality service is important to attracting ridership (Tyndall, 2018) and the loss of fare revenue could necessitate corresponding service cuts. However, fares typically comprise only a small share of agency revenue. In 2024, the average US transit agency funded 13% of operating expenditures through fares (Federal Transit Administration, 2025). Large agencies tend to raise relatively more from fares than small agencies, pulling up the average. For the median agency the "farebox recovery ratio" was only 6%. The large majority of transit funding comes from other sources including local tax revenue or state and federal grants. Still, without replacing lost revenue, fare elimination could necessitate modest service cuts, which will be particularly harmful to those most dependent on transit service. If agencies have the financial ability to forego fares, arguably, that money might be of greater value to transit users if invested in service improvements rather than fare elimination. The funding structure and politics of public transportation provision suggests that the determinants of expenditure level are complex and the loss of fare revenue does not necessitate an equivalent reduction in transit investment. Below, I empirically estimate changes in level of transit service, operating expenditure and external funding that follow fare elimination.

Fare elimination schemes have not been widely studied in the literature because they have not been widely adopted (Keblowski, 2019). European jurisdictions have hosted some significant fare-free systems, but the academic literature is limited. Luxembourg and Malta have both adopted free transit nationally. The cities of Tallinn, Estonia; Hasselt, Belgium; and Dunkirk, France have all had periods of fare-free transit. De Witte et al. (2006) broadly examines fare subsidies across Belgium, including fare-free programs, finding a positive ridership response. A German program that offered riders unlimited transit for a month for only 9 Euros was studied in Andor et al. (2025) and Rozynek (2024). Both studies found the program induced large increases in mobility, particularly for leisure activities. Fearnley (2013) summarized European experiences with fare-free transit, finding large ridership increases but limited evidence of reduced car use.

Tallinn, Estonia is perhaps the most well known instance of fare elimination. Tallinn eliminated all public transit fares for local residents in 2013, though it maintained fares for non-residents, requiring the continuation of fare collection infrastructure. Cats et al. (2014) estimated only a 1.2% increase in ridership four months after fares were eliminated, and Cats et al. (2017) subsequently estimated a 14% increase after a year of fare-free service, finding larger mobility benefits for low-income residents. Due to the details of tax policy in Estonia, fare elimination actually led to a net increase in municipal revenue. Estonians responded to the policy by strategically declaring Tallinn residency to qualify for a free transit pass, which inflated the city's official population, raising federal remittance payments.[1]

US studies of fare-free transit are also scarce. One type of fare-free program that has been widely adopted in the US is providing free transit to university students. Brown et al. (2001, 2003) provided analysis of these programs, finding student ridership

[1]See Hess (2017) for a detailed summary of research on fare-free transit in Tallinn.

increased dramatically when fares were eliminated, with estimates ranging from 71-200% across systems. Results also suggested substitution away from vehicle trips, with fare-free programs leading to reduced campus parking demand.

Ofosu-Kwabe et al. (2024) provides the only national analysis of free-fare programs in the US, finding fare removal increased ridership in small markets by 34% and medium sized markets by 28%. The study period included 2011-2021 and covers only seven US systems that adopted fare-free transit during that period, with five of those adopting free fares in 2020. Because almost all of the treatment variation is confined to 2020 and 2021, it is difficult to disentangle COVID-19 pandemic effects from the policy effect of free fares. Notwithstanding the sample size limitation, the authors find a significantly positive ridership effect. Estimates on labor force participation and local inequality metrics returned null results.

Reduced transit vehicle dwell time is one possible advantage of removing fare payments. To my knowledge, there is no empirical academic literature that has documented the effect. However, internal study by the Massachusetts Bay Transportation Authority's fare-free routes found dwell times fell by 6-23% across the routes that removed fares (Massachusetts Bay Transportation Authority, 2023). Evaluation of the fare-free program for the Merrimack Valley Regional Transit Authority (Massachusetts) found dwell times were cut in half (Merrimack Valley Planning Commission, 2025).

Fare-free transit lowers commuting costs, which could increase participation in the labor force (Sanchez et al., 2004; Stoll, 1999; Tyndall, 2017). Multiple papers have reported results from randomized control trials (RCTs) where a subset of a population was randomly allocated free or discounted transit passes and labor market outcomes were tracked. Brough et al. (2022, 2025) provided results from an RCT in Seattle, which randomly provided free transit passes to individuals enrolling for social services. The study found a significant increase in transit use among recipients of free transit passes, but found no significant labor market effects. In contrast, Mbonu & Chizeck (2025) conducted an RCT in an unnamed US county and found free fares increased trips by 43% and increased the likelihood that an initially unemployed worker found a job. An RCT in Santiago, Chile randomly assigned two-week free transit passes to some study participants and found a modest (12%) increase in transit use, with generated trips concentrated during off-peak hours (Bull et al., 2021). The RCT results generally align with European studies (e.g. Rozynek, 2024) that suggest fare elimination broadly raises mobility, mainly through non-work trips.

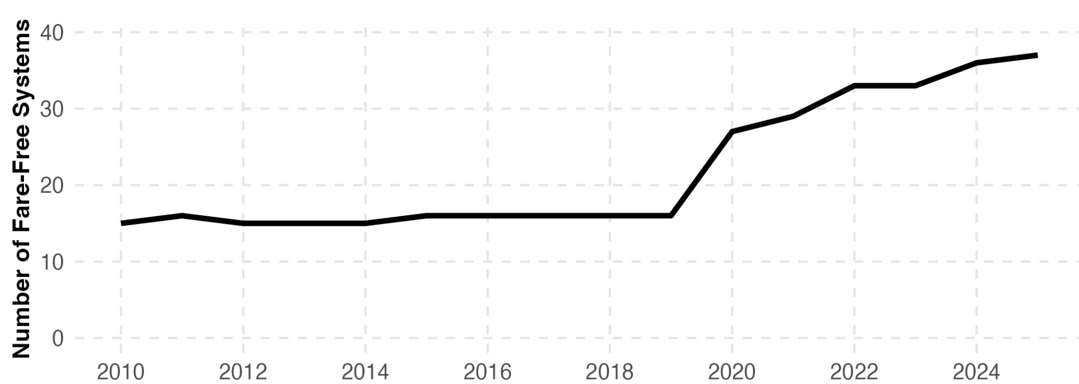
The RCT studies provide causal evidence of ridership effects. However, they identify individual-level effects, rather than the effects of system-wide fare elimination. System-wide fare elimination may have different impacts because transit agencies may endogenously adjust policy and service level in response to fare elimination. I directly estimate changes to transit agency service and finances, which is not possible in RCT designs and has not been estimated in the prior literature. Additionally, those who enroll in RCTs may be unrepresentative of the overall population. For example, Brough et al. (2022, 2025) draw participants from those already applying for public benefits. I contribute causal evidence from system-wide fare elimination programs in the US, which allows me to study general ridership consequences, as well as agency responses.

The paper will proceed as follows. Section 2 discusses the rise of fare-free transit in the US. Section 3 discusses data sources. Section 4 lays out the staggered difference-in-difference and synthetic control methods adopted in this paper. Section 5 presents results and Section 6 concludes.

2 The Expansion of Fare-free Transit in the US

The number of US transit systems operating fare-free has been growing. In 2019, among mid-to-large-sized[2] US transit agencies, only 16 operated without fares. By 2025, that number had grown to 37–a 130% increase. Figure 1 displays the total number of US transit agencies offering fully fare-free service over time. I provide a full list of identified fare-free agencies in Appendix A.

Figure 1: Number of US Fare-Free Transit Systems Over Time



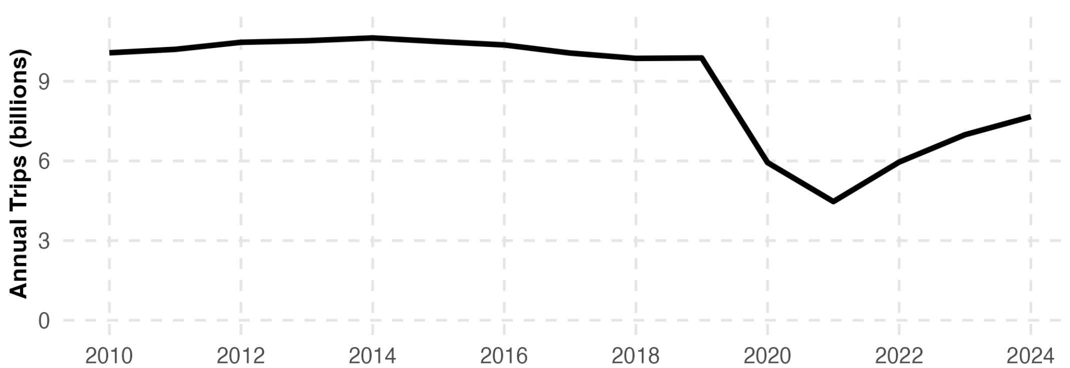
Active fare-free systems by year (2010-2025) for agencies with 2010 ridership above 500,000.

[2]I limit the analysis of this paper to agencies with 2010 ridership that exceeded 500,000.

The COVID-19 pandemic, which triggered a steep decline in transit ridership across the country, was a major catalyst for the shift towards fare-free models. Many agencies responded to the pandemic by suspending fares, initially as a temporary measure. Some of these agencies subsequently adopted fare-free service on a long-term or permanent basis. This paper focuses on systems that sustained fare-free policies for multiple years.

The pandemic was a significant shock to ridership and transit systems in general. Figure 2 shows annual transit trips across all US agencies. Ridership plummeted during the pandemic, falling by 55% between 2019 and 2021. By 2024, it had begun to rebound but remained 22% below pre-pandemic levels. Disentangling the effects of the pandemic from those of fare elimination presents a significant empirical challenge, which I discuss below.

Figure 2: Unlinked Passenger Trips for US Transit Agencies



Data includes all US transit agencies that reported information to the National Transit Database in 2024.

Persistent low ridership may itself be a motivation for eliminating fares. Many US transit systems are currently operating with excess capacity and collecting substantially less fare revenue than in the past, making the case for a zero-fare model more compelling.

3 Data

The primary data source is the National Transit Database (NTD) Service Data and Operating Expenses Time Series, provided by the Federal Transit Administration (FTA). The NTD presents data collected from federally mandated reporting requirements that apply to all transit agencies receiving federal funding. The data covers essentially all transit agencies in the country, with data coverage beginning in 1991.

The most recent release included 2,175 transit agencies who reported ridership data for 2024.

The NTD provides annual estimates on ridership, service levels, and expenditures by public transit agency. While data coverage has changed over time, I obtain consistently reported data covering 2010-2024. I drop a number of observations from analysis. First, I drop agencies that recorded fewer than 500,000 boardings in 2010. The NTD includes local systems operated by universities, corporate entities, or systems exclusively for use by those with disabilities. Elimination of fares in such systems might have very idiosyncratic consequences that are not generalizable. Additionally, fare information for very small systems are not always publicly available, complicating the identification of fare-free systems. By keeping only systems with ridership above 500,000 I am able to make conclusions that are more broadly applicable to mid-sized transit agencies. I identify 427 agencies with ridership of 500,000 or greater in 2010. I drop agencies that have incomplete data, most commonly because they did not exist across the entire 2010-2024 study period. I also drop agencies that operated fare-free service, but the elimination of fares happened outside of the study window. The exclusion allows me to construct a control group exclusively from fare charging agencies. The final data set is a 15-year balanced panel of 407 transit agencies.

Table 1 provides agency-by-year level summary statistics. There is a wide range of agency characteristics. The NTD reports annual "Unlinked Passenger Trips" for every transit system, which will serve as my primary measure of ridership. While journeys that require connections between multiple transit vehicles will represent multiple "unlinked" trips, many transit agencies do not have the capacity to track complete passenger journeys, meaning unlinked trips are the best consistent measure of system ridership. Agency-by-year ridership ranges in the final data set from only 2,400 trips (some agencies dramatically reduced service during the pandemic) to 3.5 billion trips (recorded by the New York City, Metropolitan Transportation Authority in 2014).

The NTD also records service levels. I adopt two measures of transit service level: Vehicle Revenue Miles, which counts the combined miles traversed by all transit vehicles while they provided service, and Vehicle Revenue Hours, which counts the total number of hours transit vehicles were providing service, summed over all vehicles in the system. Additionally, I make use of records on Total Operational Expenditures, which records the annual operating budget of every agency in each year.

I also use the FTA's Total Funding Timeseries dataset, which records all funding sources allocated to each transit agency. I report the total annual funding directed

Table 1: Transit Agency Panel Summary Statistics

	Mean	SD	Min	Max
Fare-free (dummy)	0.01	0.11	0.00	1.00
Unlinked Passenger Trips (millions)	21.16	158.80	0.00	3,545.17
Vehicle Revenue Miles (millions)	9.15	29.39	0.01	510.26
Vehicle Revenue Hours (thousands)	618.00	2116.00	1.00	37,351.00
Total Operational Expenditures (millions $)	108.36	478.55	0.73	10,685.05
Funding - Total (millions $)	166.72	734.51	0.73	16,758.70
Funding - Federal (millions $)	35.81	160.65	0.00	5,947.43
Funding - State (millions $)	36.90	211.00	0.00	6,110.28
Funding - Local (millions $)	53.44	188.44	0.00	3,132.53
Funding - Other (millions $)	40.57	289.15	0.00	7,208.31
Trips per Vehicle Revenue Mile	1.49	2.57	0.00	78.12
State COVID Deaths (per million pop.)	160.48	433.82	0.00	2,195.44
Year	2017	4.32	2010	2024
Observations	6,105			

The level of observation is transit agency-by-year. I include only agencies with 2010 ridership exceeding 500,000. The data covers 407 agencies from 2010-2024.

to each agency, as well as identify funding separately from Federal, State, and Local government sources, and funding from "Other" sources, which includes fare revenues. While local funding comprises the largest source, the four categories each contribute similar funding levels (Table 1). Total annual funding levels have a wide range, from $730,000 to $16.8 billion.

I manually construct a data set of fare-free transit systems. The recently published *Fare-Free Transit Evaluation Framework* by the National Academy of Sciences provides a useful list of fare-free systems (National Academies of Sciences et al., 2023), but I expand this through web searches, agency policy documents and news articles. I identify 14 US agencies that had 2010 ridership exceeding 500,000 and eliminated fares in years between 2010 and 2024, which will comprise the treated agencies in the empirical analysis.[3] Of these 14 agencies, nine eliminated fares in 2020, two eliminated fares earlier, and three eliminated fares later. I also manually collect information on the standard bus fare that was in effect before fare removal for the 14 systems. Standard

[3]Many agencies eliminated fares for brief periods in 2020 as a response to the COVID-19 pandemic. See Keblowski et al. (2023) for a detailed inventory of fare-free adoptions in the US during the pandemic. The 14 agencies I identify operated fare-free for multiple years. I do not include temporary pandemic response fare-free programs as a part of my treated sample. I discuss the potential for treatment contamination bias in 2020 when interpreting results.

fares ranged from $0.75 to $2.00. Table 2 lists the 14 fare-free agencies I identified.

Table 2: US Transit Agencies that Eliminated Fares, 2011-2023

Agency	State	Ridership (2010)	Fare-Free Start	Pre-Free Fare
Sun Tran (Tucson)	AZ	20,847,575	2020	$1.50
RideKC (Kansas City)	MO/KS	15,121,683	2020	$1.50
Greater Richmond Transit Co.	VA	14,185,511	2020	$1.50
Intercity Transit (Thurston County)	WA	5,101,082	2020	$1.25
GoDurham (Durham)	NC	5,059,368	2020	$1.00
DASH (Alexandria Transit Co.)	VA	4,352,852	2021	$2.00
Worcester RTA (WRTA)	MA	3,493,141	2020	$2.00
Merrimack Valley RTA (MeVa)	MA	2,132,657	2022	$1.25
Transfort (Fort Collins)	CO	2,074,580	2020	$1.25
Hele-On (Hawai'i County)	HI	1,301,603	2022	$2.00
Link Transit (Chelan-Douglas PTBA)	WA	1,029,155	2020	$1.00
CUE Bus (Fairfax)	VA	929,897	2020	$1.75
Mountain Line (Missoula UTD)	MT	812,955	2015	$1.00
Corvallis Transit System	OR	700,820	2011	$0.75

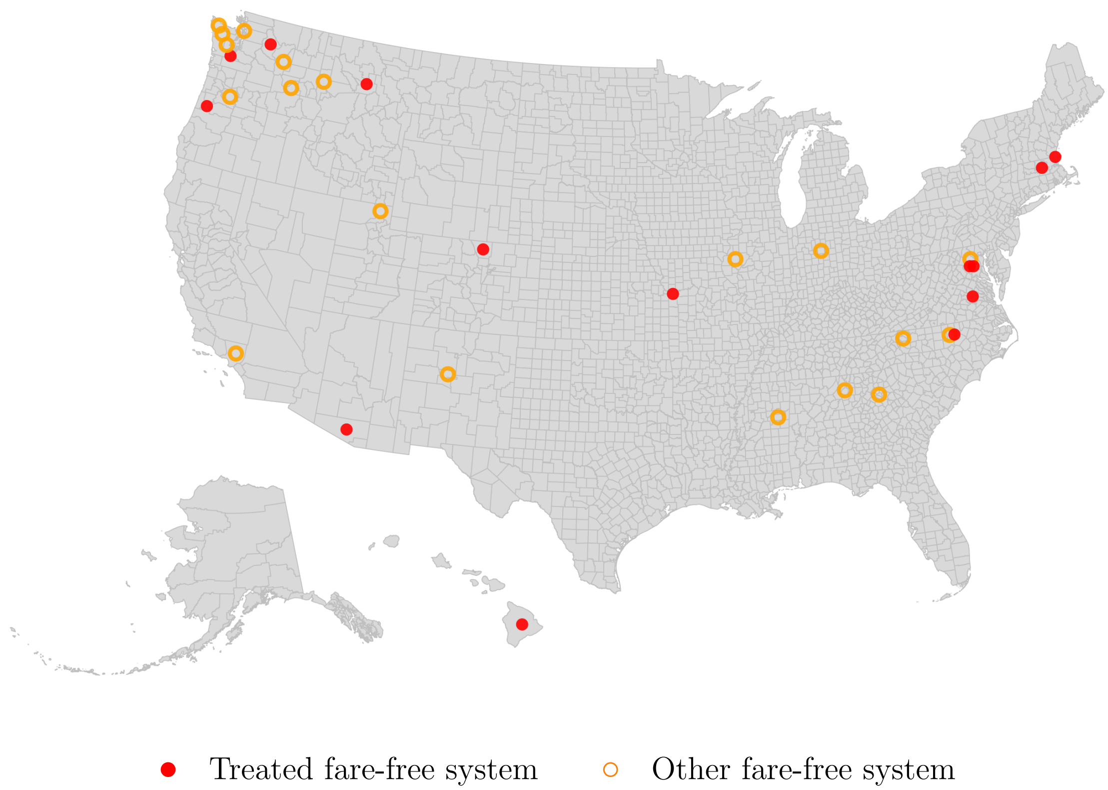
The 14 mid-sized agencies that adopted fare-free transit within the study period.

Agencies adopting fare-free transit are spread out across the US. Figure 3 maps the location of the 14 treated agencies, as well as fare-free agencies who initiated fare-free policies outside of the study period. Three treated agencies are located in Virginia, while Massachusetts and Washington each contain two. Six additional fare-free systems operate in Washington State, but they are either too small to be included in the analysis or had policy start dates outside of the study period.

While none of the nation's largest transit systems have removed fares, fare-free agencies represent a range of ridership levels. Figure 4 charts ridership across all systems in the sample, indicating those systems that removed fares in the study period with a red arrow. I show the ridership distribution for 2010, 2020 (the year many systems removed fares), and 2024 (the most recent year available). The largest system to remove fares was Sun Tran in Tuscon, AZ, recording 21 million trips in 2010, which is in the 87$^{\text{th}}$ percentile of the study sample.

Prior literature has suggested that fare-free transit might be more suitable for transit systems experiencing low service utilization (National Academies of Sciences et al., 2023). I construct a measure of utilization by dividing trips by vehicle revenue miles.

Figure 3: Location of Fare-Free Systems

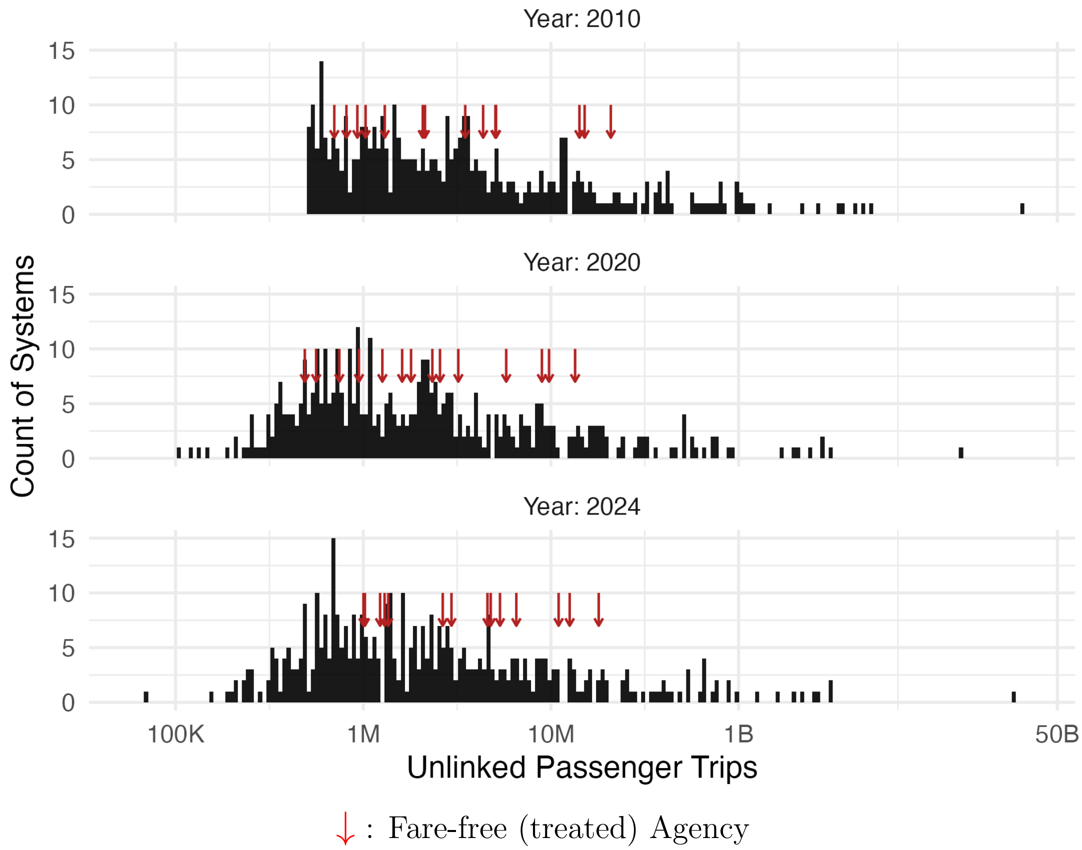


Fare-free systems operating in the US in 2024. Treated systems are limited to those with 2010 ridership of at least 500,000 and that eliminated fares during the study period. The full list of fare-free systems is provided in Appendix Table A1. County boundaries are shown.

The metric represents the number of transit boardings per mile of vehicle operation. The metric averages 1.49. Figure 5 shows the distribution of system utilization across all systems in the sample, highlighting the utilization among systems that removed fares. I do not find any clear relationship between system utilization and the probability an agency removed fares. Utilization of transit fell sharply during the pandemic, and in 2024 remained below pre-pandemic levels.

In my regression analysis I control for the potentially heterogeneous influence of COVID-19 across agencies. A correlation between the local severity of the pandemic and the probability of removing fares could be a threat to identification because pandemic severity will also impact ridership. While I cannot observe COVID-19 rates at the

Figure 4: Unlinked Passenger Trips of Sample, Log Scaled



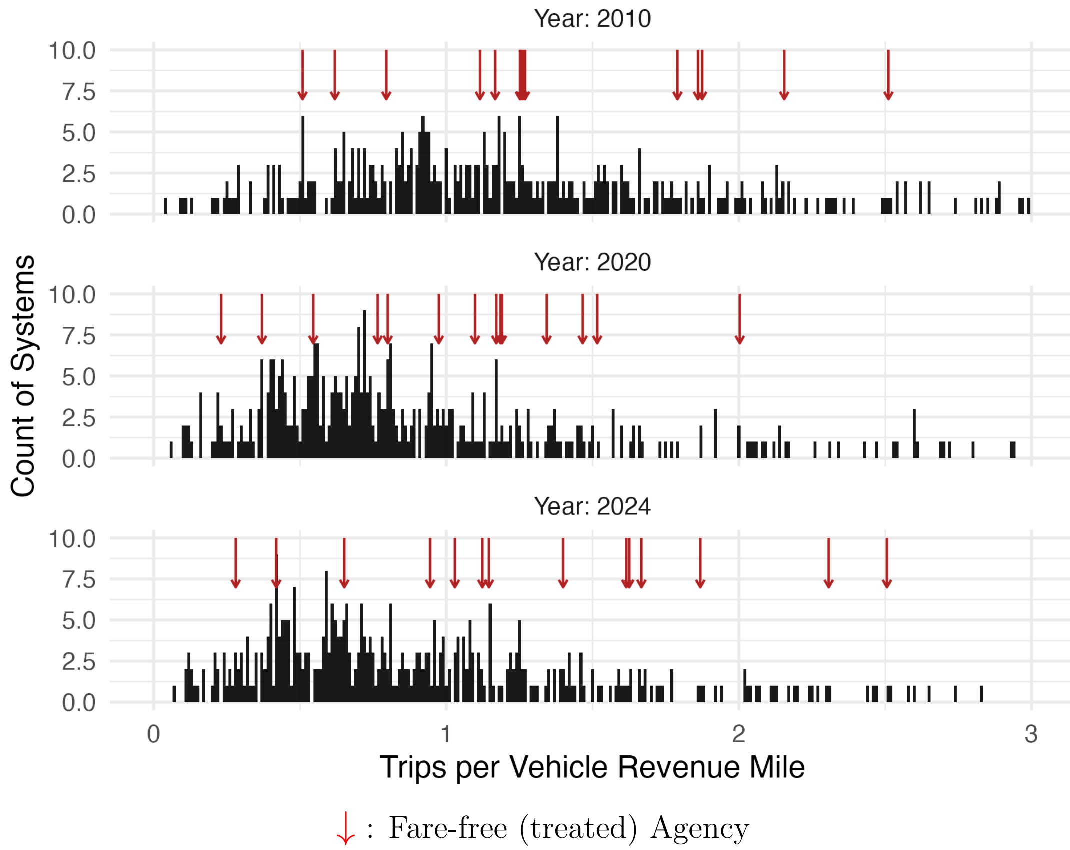
Unlinked passenger trips is equal to the number of transit vehicle boardings in a year. I include only agencies with ridership of at least 500,000 in 2010. Trips are logged in the figure. Red arrows indicate the 14 agencies that adopted fare-free transit during the study period. N = 407.

transit agency level, I make use of state level data on COVID-19 deaths from the US Center for Disease Control. I use state populations from the 2020 US Census to estimate annual COVID-19 death rates, and assign a rate to each agency based on its primary state of operation. COVID-19 death rates are available for 2020-2023, while years outside of this range are assigned a value of zero.

4 Methodology

I adopt two complementary methodologies. I first estimate the average treatment effect on the treated agencies of eliminating fares by estimating a staggered difference-in-

Figure 5: Utilization, Trips per Vehicle Revenue Mile



Utilization is measured as the number of unlinked passenger trips per total miles of transit service provided in a year. I include only agencies with ridership of at least 500,000 in 2010. Red arrows indicate the 14 agencies that adopted fare-free transit during the study period. N = 407.

difference model. Second, to investigate heterogeneity across treated systems, I generate synthetic control method estimates for each agency individually. I test for effects on ridership, service level, agency expenditures, and agency revenue.

Equation 1 outlines the staggered difference-in-difference estimation strategy.

$$\log(Y_{it}) = \beta_0 + \beta_1 F_{it} + \Omega_i + \Phi_t + X_{it}'\theta + \varepsilon_{it} \tag{1}$$

Y is the outcome variable, such as unlinked passenger trips for transit agency i in year t. F is a dummy variable that takes a value of one if the agency offers free fares in that year. Ω is an agency fixed effect and Φ is a year fixed effect. X is a vector of agency by year control variables, including the COVID-19 death rate in agency i's home state. I interpret β_1 as the effect of eliminating fares on the outcome variable. I estimate standard errors clustered at the transit agency level, which is the level of treatment.

Prior research has demonstrated that estimation of causal effects in difference-in-difference setups with staggered treatment requires an adjustment to the estimator (Goodman-Bacon, 2021; Callaway & Sant'Anna, 2021). I adopt the staggered difference-in-difference estimator proposed in Callaway & Sant'Anna (2021), which is not subject to the bias identified in Goodman-Bacon (2021).

The staggered difference-in-difference approach aims to provide a causal interpretation of the policy's effect on agency outcomes by controlling for agency specific characteristics and national year-to-year changes, while also establishing consistent pre-trends between treated and control observations. In addition to estimating the average treatment effect, I am also interested in the possibility that the policy impacts vary across post-treatment years. I provide results from an event study model, which relies on the same Callaway & Sant'Anna (2021) estimation method. The event study analysis provides evidence for the underlying parallel trend assumption, which assumes treated agencies had similar trends in outcomes prior to fare elimination and would have continued on similar trends if not for the policy change.

Establishing a parallel trend between treated and control observations allows for a causal interpretation of the estimated effect. Simply comparing ridership before and after fare-free adoption, which is a typical approach for transit agency internal evaluations, could provide misleading results. In particular, the impact of the COVID-19 pandemic on ridership generates significant annual changes across the study period. Failing to control for time-specific national levels of ridership would bias results. For the 14 systems I study, comparing ridership the year before fare elimination to ridership one year following free-fare adoptions shows that the average system saw a 27% *decrease* in ridership. However, this estimate is significantly impacted by the contaminating effect of the pandemic.

To identify agency specific effects, I subsequently estimate a synthetic control model, which I apply to each of the 14 systems being studied. I use a standard synthetic control method setup following the applications in Abadie et al. (2010) and Abadie & Gardeazabal (2003) and use the algorithm provided in Abadie et al. (2011). For each treated agency, I construct a donor pool consisting of non-treated agencies whose 2010 ridership was within 50% to 150% of the treated agency's 2010 ridership. I estimate synthetic control weights based on each pre-treatment year's ridership level. The method has two benefits, (1) synthetic control weights allow for a better pre-treatment match for the treated agency, which can be confirmed graphically. Comparing treated agencies to other agencies that were on very similar ridership trajectories provides a plausible identification strategy, and (2) the method produces agency specific estimates that capture treatment effect heterogeneity across agencies. I use these agency specific estimates to present correlations between realized ridership effects and plausible predictors of the efficacy of fare elimination. I test whether initial system size, initial system utilization rate, initial fare level, and concurrent service cuts or expansions explain differing ridership effects.

An additional estimation method that is well suited for policy evaluation in cases of small treatment populations is the *Synthetic Difference-in-Difference* approach outlined in Arkhangelsky et al. (2021). The method combines a difference-in-difference setup with control group weighting to improve pretrend matching. However, the method is not well suited for staggered treatment settings, meaning it can only be applied to the set of agencies with a common treatment year. As a robustness check, I provide results from this estimating methodology in Appendix B.

By providing results from multiple estimation strategies I am able to provide robust evidence for the estimated effects. I find estimates are in strong agreement across the approaches.

5 Results

I first present results from the staggered difference-in-difference design to estimate the effect of free bus service on ridership, service level and agency finances. Acknowledging that the effect of free service may have significant heterogeneity across systems, I then present synthetic control method results for all 14 systems separately. I subsequently compare agency characteristics to ridership changes across the systems, identifying predictors for which types of systems experienced high or low ridership changes from fare removal.

5.1 Staggered Difference-in-difference Results

Table 3 presents the main results of the Equation 1 staggered difference-in-difference specification. Column 1 shows the estimated change in unlinked passenger trips for agencies adopting fare-free transit. I estimate that fare elimination caused a 46% increase in trips for the average treated system. The effect is highly statistically significant. Plausibly, the impact of ridership changes associate with the COVID-19 pandemic could confound results. Column 2, includes a control variable for the COVID-19 death rate at the state-year level. Including this control variable has no effect on the estimated result. Removal of fares could necessitate a change in service level, which in turn affects ridership. In column 3, I control for service level with separate covariates for vehicle revenue miles, vehicle revenue hours, and agency operating expenditure. The estimate increases slightly, to 47%. The stability of the estimate suggests the estimated effect reflects a causal effect of fare elimination and is not due to endogenous local COVID-19 prevalence or endogenous changes in the agency's level of service.

Table 3: Impact of Free Transit on Ridership and Service Level

	Unlinked Trips	Unlinked Trips	Unlinked Trips	Vehicle Revenue Miles	Vehicle Revenue Hours	Operating Expenditure
	(1)	(2)	(3)	(4)	(5)	(6)
Fare-free System	0.380**	0.380**	0.387**	0.100*	0.117**	0.092*
	(0.074)	(0.074)	(0.073)	(0.039)	(0.034)	(0.041)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Agency fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
State COVID control	No	Yes	Yes	Yes	Yes	Yes
Service level controls	No	No	Yes	No	No	No

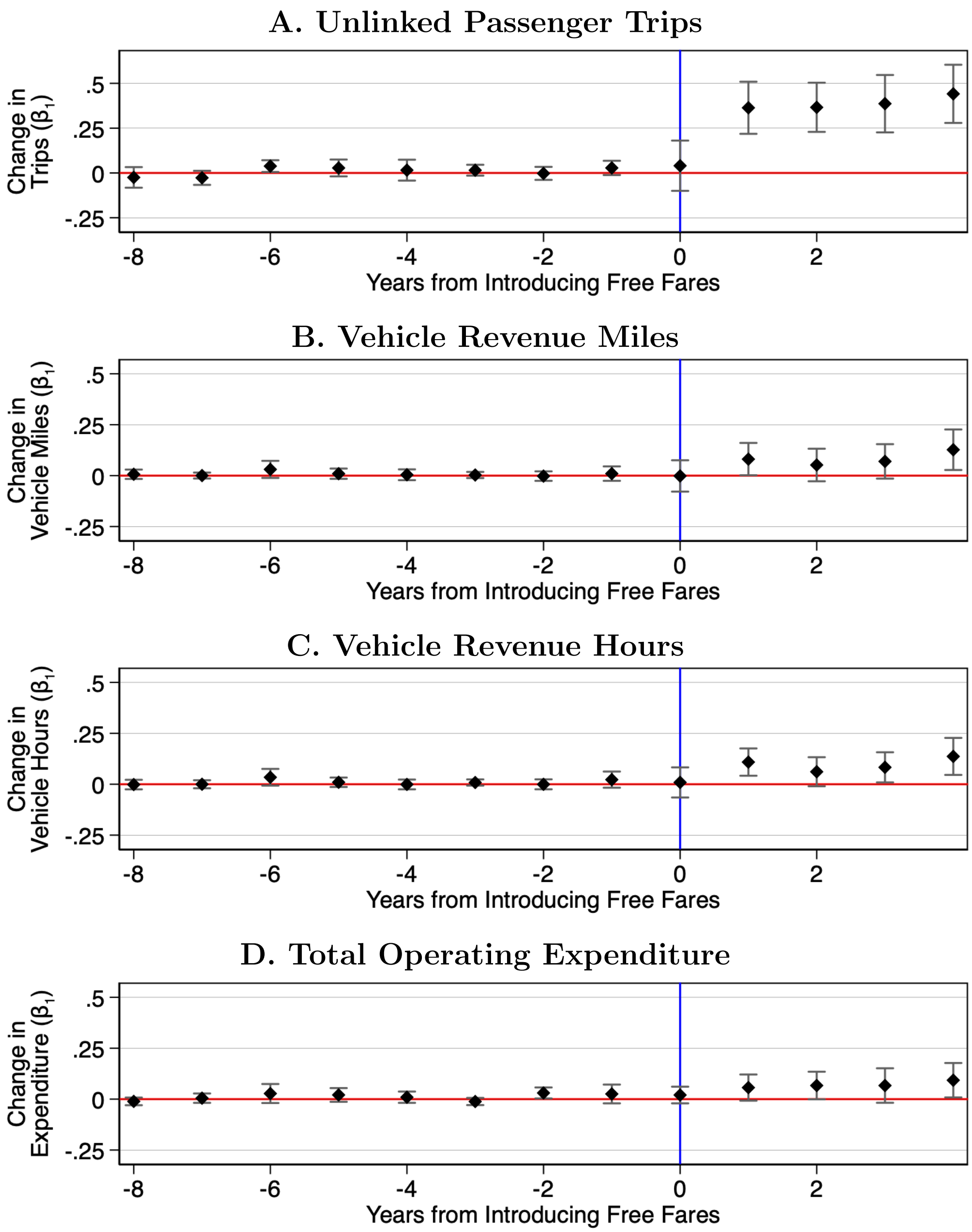
N = 6,105. Robust standard errors clustered at the agency level are shown in parentheses. ** p<0.01, * p<0.05.

The staggered difference-in-difference methodology can also be adapted to an event study. Figure 6 provides event study results. Year zero represents the year fare-free service was introduced and is therefore partially treated. I find no effect on ridership in year zero.[4] In post-treatment years one, two, three and four, I find ridership is increased by 44%, 44%, 47% and 55% respectively. I only observe two agencies with more than four post-treatment years, so I am not able to reliably estimate longer term outcomes. The result shows that the elimination of fares generates a large ridership effect during the first full year of fare-free service, with weak evidence that the effect grows over time.

[4]As the majority of treated agencies removed fares in 2020, Year 0 as well as Year 1 estimates could be contaminated by instances where control agencies introduced short-term fare elimination programs as a COVID response. The stability of estimates in latter treatment years suggests this is not a significant source of bias.

I take 55% to be the long-run impact of fare elimination on ridership.

Figure 6: Staggered Difference-in-difference Event Study Results



Results of the staggered difference-in-difference estimation are displayed as event study figures. I control for COVID-19 death rate at the state-year level in all panels. Year 0 is partially treated, with fare elimination occurring at some point during that year, while later years are fully treated. 95% confidence intervals are shown.

The estimates rely on a larger sample of fare-free agencies and cover a longer post-treatment time period than prior studies in the literature. The estimated ridership effect is nearly double the effect estimated in Ofosu-Kwabe et al. (2024), who estimated a 28% ridership increase in medium sized US markets and 34% in smaller markets. The estimates are significantly larger than those evaluating fare elimination in Tallinn (Cats et al., 2014, 2017).

I use the same difference-in-difference methodology to evaluate the impact of fare elimination on level of transit service. Table 3 columns 4-6 present level of service results. Column 4 estimates the effect on vehicle revenue miles. I estimate a significant 10.5% increase in vehicle revenue miles after fare elimination. For vehicle revenue hours I estimate a statistically significant 12.4% increase (column 5). In column 6, I estimate an effect on the annual operating expenses of the transit agency and find fare-free adoption is associated with a significant 9.7% expenditure increase. Overall, I find evidence that the agencies that removed fares simultaneously underwent service expansion, relative to control agencies. The result is potentially counter-intuitive as these agencies lost fare revenue but were still able to expand expenditures. The result suggests that agencies were able to more than compensate for the revenue loss by exploiting other sources of funds. I provide evidence for this funding mechanism below.

Event study results for service level and expenditures are provided in Figure 6 panels B-D. Together, these results suggest that fare elimination is associated with higher service and higher spending on transit. Four years after fare elimination, all three metrics of service level are statistically significantly higher in treated agencies than control agencies. Unlike the ridership estimates, which represent a demand response, effects on service level are likely endogenous to the decision to eliminate fares. Agencies who eliminate fares are likely interested in expanding public transit use and may be raising service levels as part of a long term expansion plan that includes fare elimination. While some past research has argued that fare elimination will result in service cuts due to deteriorating agency budgets (Storchmann, 2003), this phenomenon does not appear in the data. However, I am only able to estimate service level effects up to four years after fare-free adoption. Conceivably, lost revenue from removing fares could lead to service cuts over longer time horizons, but there is no empirical evidence for this in the US context.

I find the loss of fare revenue is not accompanied by a decline in expenditure, suggesting agencies recoup lost revenue by tapping alternative sources. Table 4 estimates the staggered difference-in-difference model on total annual funding secured by the agency (Column 1), as well as separate estimates for Federal, State, Local, and Other funding categories (Columns 2-5), and funding devoted separately for Operating and Capital expenses (Columns 6-7). I estimate fare elimination leads to a positive 5.0% increase in overall funding, but the result is not statistically significant. Funding allocations can be volatile across years as government grants commence and expire over time, which adds an additional layer of noise to data that was already relying on a small treatment sample. Therefore, estimates of fare elimination on annual funding amounts tend to have large standard errors. I find positive effects on Federal and State funding, but the results are also statistically insignificant. I do find a significant and positive impact on local funding. I estimate local funding allocations to the transit agency rose by 56% for the average treated agency after fare elimination (column 4). I find a large and significant 77% drop in "Other" funding sources. "Other" funding is primarily composed of fare revenue, which explains the large decline. However, "Other" also includes revenues generated from such sources as advertising contracts, concession sales, park-and-ride facility charges or any other revenue sources the transit agency collects directly.

Table 4: Impact of Free Transit on Log of Agency Funding

	Total (1)	Federal (2)	State (3)	Local (4)	Other (5)	Operating (6)	Capital (7)
Fare-free System	0.049	0.301	0.767	0.447*	-1.448*	0.084*	0.063
	(0.072)	(0.482)	(0.722)	(0.185)	(0.574)	(0.036)	(0.602)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agency fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State COVID control	Yes	Yes	Yes	Yes	Yes	Yes	Yes

N = 6,105. Robust standard errors clustered at the agency level are shown in parentheses.
** p<0.01, * p<0.05.

Large standard errors prevent providing a clear story about which level of government is typically responsible for compensating the agency for lost fare revenue. While the increase in local funding is the only statistically significant result, the point estimate for state funding implies that state funding more than doubles, on average. Overall, the results suggest the average agency is able to expand government transfers when eliminating fares, though experiences differ considerably across agencies as to what source of external funding is tapped.

Table 4 columns 6-7 breaks out funding received by money devoted to operating versus than capital expenditures. I find that funding devoted to operating expenses increased by a significant 8.7%, while I find a positive but statistically insignificant effect on capital project funding. An increase in operating expenses is consistent with service expansion after fare elimination. I find no evidence that agencies shift funding away from capital investments to cover expanded service.

5.2 Synthetic Control Method Results

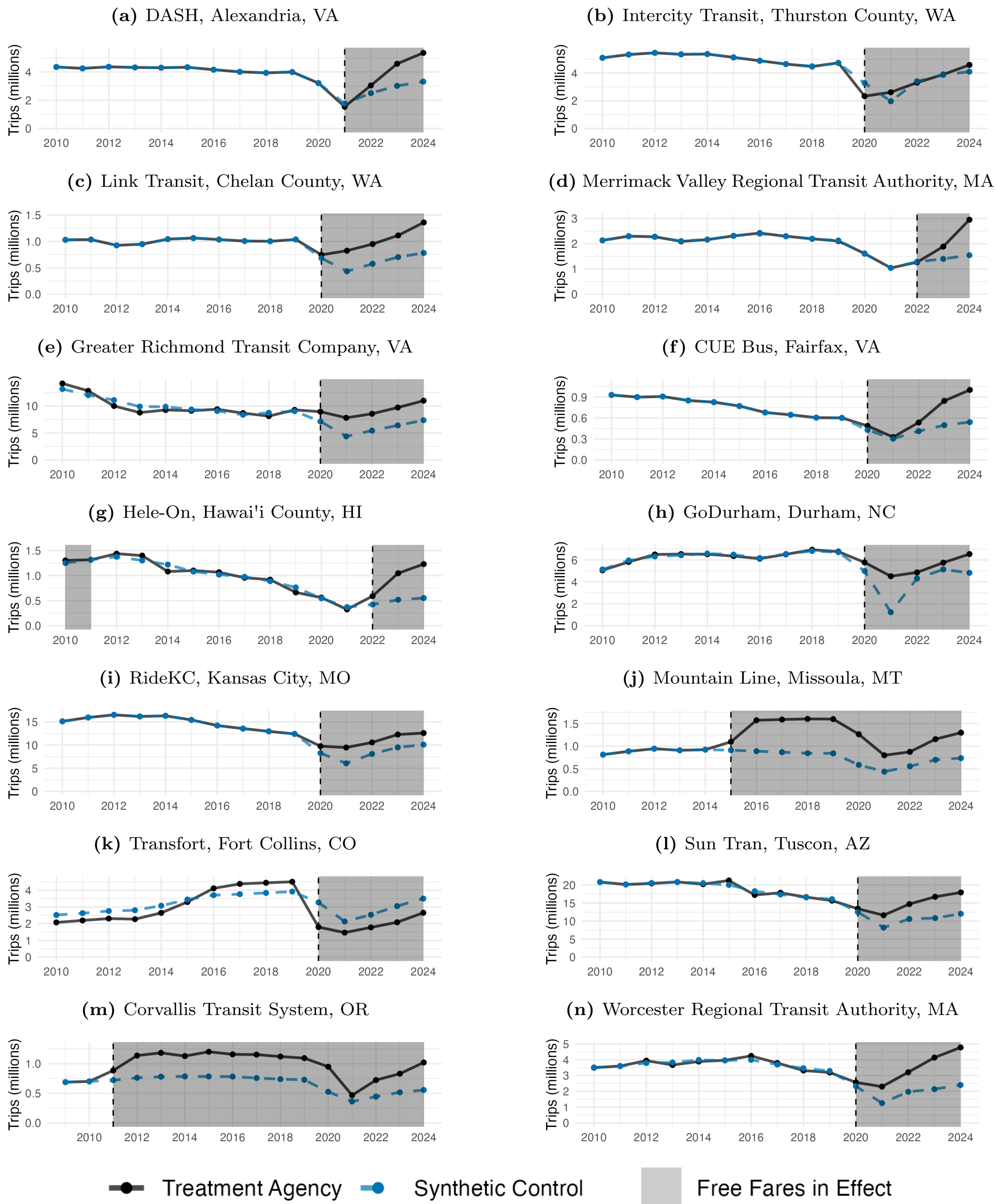
The previous section establishes that fare elimination leads to large ridership gains and a significant increase in an agency's level of service, on average. I now apply a synthetic control method to yield agency specific estimates. Some prior research on fare-free systems suggests benefits are strongest for small systems (Ofosu-Kwabe et al., 2024) or systems with low initial utilization (Fearnley, 2013). Estimating agency specific effects allows me to compare these to agency characteristics.

Figure 7 displays estimates of ridership changes from fare elimination for all 14 systems based on the synthetic control method.[5] For 13 of 14 systems, I estimate an increase in ridership. I find the average system experienced 60% growth in ridership due to fare elimination, with the median estimated as 68%. These estimates are slightly larger but consistent with the 55% increase estimated under the staggered difference-in-difference model. Estimates range from -24.2% (Transfort, Fort Collins, CO) to +122.8% (Hele-On, Hawai'i County, HI). A negative ridership effect is consistent with capturing the impact of concurrent service cuts due to fare elimination. The synthetic control method does not control for confounding variables that happened simultaneously with fare elimination, so changes that are unique to an adopting agency at the time fares were eliminated will affect results. In particular, reducing level of service concurrently with fare elimination could show up as a negative ridership effect if the impacts of service cuts are larger than the impacts of eliminating fares.

In addition to estimating ridership effects, I use the synthetic control method to estimate level of service effects of fare elimination for all 14 systems. Figure 8 provides the estimated change in vehicle revenue miles attributable to fare elimination. I estimate vehicle revenue miles increased in eight of 14 systems. However, agencies

[5] I adjust the method in two instances. The Hele-On system in Hawai'i County had two discrete periods of fare-free service, spanning 2005-2011 and 2022-2025. When generating donor pool weights for Hele-On, I omit 2010 and 2011 and only identify the effect of the second period of fare-free service. The Corvallis Transit System began operating fare-free in 2011. The study period of 2010-2024 would only allow for a single pre-treatment year. I therefore extend the pre-treatment period for the Corvallis Transit System to 2009 to allow matching of pre-treatment trends. All fare-free periods are highlighted in Figure 7.

Figure 7: Synthetic Control Results, Annual Unlinked Passenger Trips



Each panel represents a separate synthetic control method result. Control group weights are generated to match pre-treatment ridership level and trends.

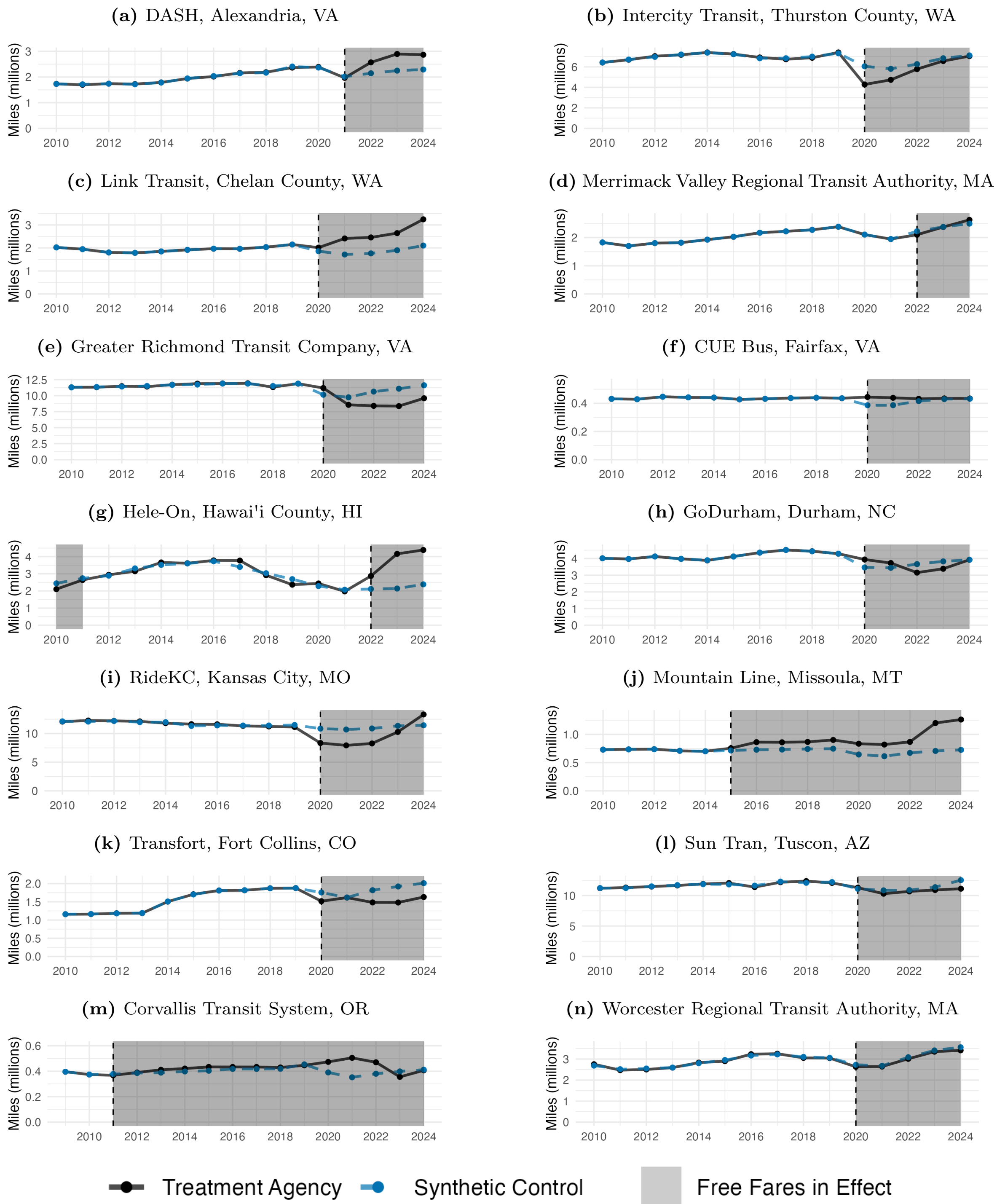
that did increase service tended to increase it substantially. Across all agencies, the average change was a 14.7% increase in vehicle revenue miles. For the two agencies with at least nine years of post-treatment data I can estimate longer run effects. After nine years of free-fares, I estimate the Mountain Line (Missoula, MT) had a level of service 74% higher than control group agencies. However, after 13 years, the Corvallis Transit System (Oregon) had a level of service that was roughly the same as control agencies. These different experiences highlight the idiosyncrasy in how service level relates to fare elimination. Across the 14 systems, estimated changes in service level ranged from -18.9% (Transfort, Fort Collins, CO) to +84.0% (Hele-On, Hawai'i County, HI). Figure 8 indicates that many agencies maintained roughly the level of service that would have been expected had they not eliminated fares, while there are some instances of significant expansion. While different agencies had different responses, there is no evidence of systematic service cuts in response to fare elimination, at least during the limited post-treatment period.

The overall results are consistent between the staggered difference-in-difference and synthetic control methods. In Appendix B, I provide additional results for ridership and service level changes from a *Synthetic Difference-in-difference* design (Arkhangelsky et al., 2021). The results are consistent.

Fare elimination likely has different ridership effects based on the initial conditions of the agency. Figure 9 displays the correlation between each agency's estimated ridership change due to fare elimination (as estimated by the system's final period presented in Figure 7) and various agency characteristics. Panel A explores the relationship between agency size, measured by 2010 ridership, and the magnitude of the fare policy's impact. I find that smaller agencies tended to experience larger ridership gains, consistent with Ofosu-Kwabe et al. (2024); however, the relationship is not statistically significant. Panel B examines 2010 system utilization as a proxy for excess capacity. It is plausible that agencies operating below capacity could more easily accommodate new riders and capture larger ridership gains. However, I find no statistically significant association between pre-treatment utilization and the ridership impact of fare elimination. Panel C considers the effect of pre-treatment fare levels, which ranged from \$0.75 to \$2.00 (see Table 2). Removing fares might have a larger impact for systems that had high fares to begin with. The results suggest that a \$1.00 increase in pre-treatment fares is associated with a 28 percentage point larger increase in ridership. However, due to the small sample size, this effect is also statistically insignificant.

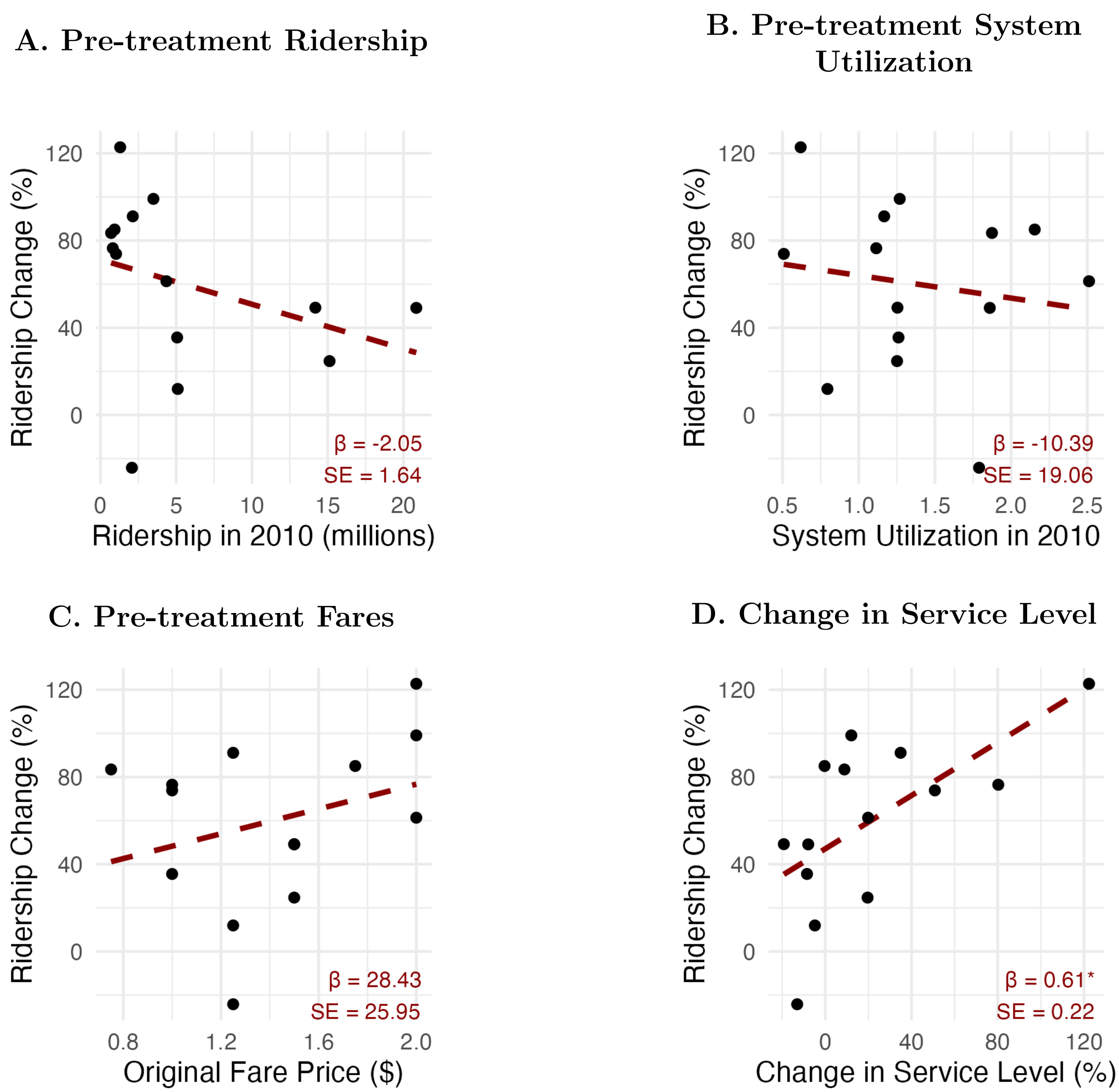
Finally, Panel D investigates the relationship between service level changes and

Figure 8: Synthetic Control Results, Vehicle Revenue Miles



Each panel represents a separate synthetic control method result. Control group weights are generated to match pre-treatment vehicle revenue mile levels and trends.

Figure 9: Correlation of Ridership Change and System Characteristics



Each panel displays the correlation between the percent change in unlinked passenger trips attributable to fare elimination as calculated by the synthetic control method, compared to possible predictors of the efficacy of fare removal. Ordinary Least Squares lines of best fit are shown with bivariate regression coefficients.

the effect of fare removal. Service level is proxied by the percent change in vehicle revenue miles between the year before fare elimination and the final year of observation. Here, I find significant evidence that agencies reducing service at the same time as implementing fare-free policies saw smaller ridership gains. Specifically, a 10% cut in service is associated with a statistically significant 6.1 percentage point reduction in the ridership increase attributable to fare elimination. The agency that expanded service the most (Hele-On, Hawai'i County, HI) also experienced the largest post-treatment ridership gains. Whereas the five agencies that cut service all experienced among the smallest ridership gains.

The only system where fare elimination appeared to reduce ridership (Transfort, Fort Collins, CO) simultaneously cut service by 13%. Transfort also had charged only $1 fares prior to fare elimination, which made the policy change less impactful. While the analysis reveals that maintaining service level is important to realizing ridership gains from fare elimination, I find no evidence, across methodologies, that fare removal is typically followed by reductions in service.

In the staggered difference-in-difference analysis I estimate fare elimination triggers a ridership increase of 47%, when averaged across post-treatment years (Table 3). The estimate is conditional on changing service level. Changes to service level were small and varied enough that controlling for service level did not significantly affect the main estimate. However, zooming in on individual agencies reveals that the ridership gain realized by an agency partially depends on the agency's choice in maintaining or expanding level of service.

5.3 Limitations

The analysis of this paper has some limitations. While fare-free programs have expanded in the US, there are still relatively few examples to be studied. I provide the most expansive evaluation of system-wide fare-free transit programs in the US. However, my sample includes only 14 adopting systems, which limits statistical power in the analysis. While these 14 instances cover a wide range in terms of system size, utilization, and geographic locations, the experiences of systems that are, for example, significantly smaller or larger may differ when removing fares. Because fare-free policies have been adopted recently, I am only able to estimate effects up to four years post-treatment. I address a significant policy concern with fare-free programs: that the lost revenue may lead to reductions in service. While I don't find any evidence of service reductions in the first four years, there is limited data to estimate longer run effects. Finally, I am unable to observe the characteristics of induced trips. While these trips must each have a positive welfare effect on the rider (their revealed preference is that the trip was beneficial) these trips are also likely to be of a lower welfare benefit than trips taken under a system with fares (their revealed preference was to not take these trips when fares were in effect). Past research suggests free transit trips may have high social value but limited labor market impacts (Rozynek, 2024; Brough et al., 2025). A deeper understanding of the characteristics of trips induced by fare elimination in the US context would be an important topic for further research.

6 Conclusion

In economic terms, transit fares are a user fee. While user fees generate revenue, they also suppress demand. Theoretically, removing fares should increase ridership while triggering lower revenue, expenditure and service quality. However, the empirical evidence differs. Ridership increases are clear–the average agency expanded ridership by 56%. However, service and expenditure both tended to increase after fares were removed. I find service level and overall expenditure increased by roughly 10%, on average, after fares were removed.

The fiscal shock of fare elimination to the transit agency appears to be small. One explanation is that fares were a relatively small fraction of agency revenue to begin with. For treated agencies, farebox collections averaged 17% of operating budgets at the start of the study period. The percentage overstates the importance of fares, as some of that revenue must be devoted to funding fare collection itself. For example, an internal evaluation by one treated agency estimated that 27% of its 2019 fare revenue was consumed by the costs of collecting fares (Merrimack Valley Planning Commission, 2025).

Eliminating transit fares has the potential to substantially reshape urban mobility and improve equity outcomes. Funding transit through general taxation would bring it in line with other public services, such as libraries, public schools, and roadways, that are typically free at the point of use. In each of these domains, charging a user fee would raise revenue but suppress demand, particularly among low-income populations. Libraries, for instance, operate without fees because imposing fees would likely be seen as unjust and inequitable. The choice to charge fares for a ride on a bus but not for a book at a library does not reflect a fundamental economic distinction: both services involve high fixed costs and low marginal costs. Instead, the decision to impose user fees represents a policy trade-off between the equity and welfare benefits of broad public access and the goal of generating revenue.

Historically, public transit in the US was operated by private, profit-seeking firms that charged fares to recoup capital investments. When public agencies began taking over transit service provision in the latter half of the 20th century they retained the fare model. Public acceptance of transit fares may therefore stem more from historical precedent than economic necessity.

Fare-free transit remains a relatively new policy in the US, but it is expanding. Beyond the agencies studied above, additional agencies have recently enacted local ordinances to initiate fare-free service. Notable examples include the City of Albuquerque, which removed fares in 2024, and Montgomery County, Maryland, where the *Ride On* system eliminated fares in 2025. New fare-free programs offer valuable opportunities for continued policy research, with the potential to deepen our understanding of fare-free transit's impacts on mobility, equity, and broader societal outcomes.

References

Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American Statistical Association*, 105(490), 493–505.

Abadie, A., Diamond, A., & Hainmueller, J. (2011). Synth: An R package for synthetic control methods in comparative case studies. *Journal of Statistical Software*, 42, 1–17.

Abadie, A. & Gardeazabal, J. (2003). The economic costs of conflict: A case study of the Basque Country. *American Economic Review*, 93(1), 113–132.

Albalate, D., Borsati, M., & Gragera, A. (2024). Free rides to cleaner air? Examining the impact of massive public transport fare discounts on air quality. *Economics of Transportation*, 40, 100380.

Andor, M. A., Dehos, F. T., Gillingham, K. T., Hansteen, S., & Tomberg, L. (2025). Public transport pricing: An evaluation of the 9-Euro ticket and an alternative policy proposal. *Economics of Transportation*, 42.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., & Wager, S. (2021). Synthetic difference-in-differences. *American Economic Review*, 111(12), 4088–4118.

Brough, R., Freedman, M., & Phillips, D. C. (2022). Experimental evidence on the effects of means-tested public transportation subsidies on travel behavior. *Regional Science and Urban Economics*, 96, 103803.

Brough, R., Freedman, M., & Phillips, D. C. (2025). Eliminating fares to expand opportunities: Experimental evidence on the impacts of free public transportation on economic and social disparities. *American Economic Journal: Economic Policy*, 17(3), 1–34.

Brown, J., Hess, D. B., & Shoup, D. (2001). Unlimited access. *Transportation*, 28(3), 233–267.

Brown, J., Hess, D. B., & Shoup, D. (2003). Fare-free public transit at universities: An evaluation. *Journal of Planning Education and Research*, 23(1), 69–82.

Bull, O., Munoz, J. C., & Silva, H. E. (2021). The impact of fare-free public transport on travel behavior: Evidence from a randomized controlled trial. *Regional Science and Urban Economics*, 86, 103616.

Callaway, B. & Sant'Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2), 200–230.

Cats, O., Reimal, T., & Susilo, Y. (2014). Public transport pricing policy: Empirical evidence from a fare-free scheme in Tallinn, Estonia. *Transportation Research Record*, 2415(1), 89–96.

Cats, O., Susilo, Y. O., & Reimal, T. (2017). The prospects of fare-free public transport: Evidence from Tallinn. *Transportation*, 44(5), 1083–1104.

De Witte, A., Macharis, C., Lannoy, P., Polain, C., Steenberghen, T., & Van de Walle, S. (2006). The impact of "free" public transport: The case of Brussels. *Transportation Research Part A: Policy and Practice*, 40(8), 671–689.

Fearnley, N. (2013). Free fares policies: Impact on public transport mode share and other transport policy goals. *International Journal of Transportation*, 1(1), 75–90.

Federal Transit Administration (2025). National transportation database service data and operating expenses time series.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2), 254–277.

Hess, D. B. (2017). Decrypting fare-free public transport in Tallinn, Estonia. *Case studies on transport policy*, 5(4), 690–698.

Keblowski, W. (2019). Why (not) abolish fares? Exploring the global geography of fare-free public transport. *Transportation*, 47(6), 2807–2835.

Keblowski, W., Goldberg, D., Gillard, M., & Maciejewska, M. (2023). Missed opportunity or herald of change? The sudden rise of fare-free public transportation in the United States during the COVID-19 pandemic.

Massachusetts Bay Transportation Authority (2023). City of Boston fare free program mid program report.

Mbonu, O. & Chizeck, S. (2025). The role of the fare in welfare: Public transportation subsidies and their effects on low-income households.

Merrimack Valley Planning Commission (2025). MeVa fare-free evaluation and business case.

National Academies of Sciences, E., Medicine, et al. (2023). Fare-free transit evaluation framework.

Ofosu-Kwabe, K., Lim, S. H., & Malalgoda, N. (2024). Does fare-free transit increase labor-force participation and reduce income inequality? *Journal of Public Transportation*, 26, 100095.

Rozynek, C. (2024). Imagine the financial barrier to public transport use disappears. the impact of the 9-Euro-ticket on the mobility and social participation of low-income households with children. *Transport Policy*, 149, 80–90.

Sanchez, T. W., Shen, Q., & Peng, Z.-R. (2004). Transit mobility, jobs access and low-income labour participation in us metropolitan areas. *Urban studies*, 41(7), 1313–1331.

Schouten, A., Taylor, B. D., & Blumenberg, E. (2021). Who's on board? Examining the changing characteristics of transit riders using latent profile analysis. *Transportation Research Record*, 2675(7), 1–10.

Stoll, M. A. (1999). Spatial job search, spatial mismatch, and the employment and wages of racial and ethnic groups in Los Angeles. *Journal of Urban Economics*, 46(1), 129–155.

Storchmann, K. (2003). Externalities by automobiles and fare-free transit in Germany-a paradigm shift? *Journal of Public transportation*, 6(4), 89–105.

Tyndall, J. (2017). Waiting for the R train: Public transportation and employment. *Urban studies*, 54(2), 520–537.

Tyndall, J. (2018). Bus quality improvements and local commuter mode share. *Transportation Research Part A: Policy and Practice*, 113, 173–183.

Vieira, R., Pereira, R. H., Emanuel, L., & Alves, P. J. (2025). The effects of fare-free transit on the travel behavior of older adults. *Journal of Environmental Economics and Management*.

Webster, G. (2024). Free fare for better air? Evaluating the impacts of free fare public transit on air pollution. *Transportation Research Part A: Policy and Practice*, 184, 104076.

A Fare-free Systems

Through searches of public reports and documents I identify 37 transit systems in the US that are operating fare-free as of 2025. Table A1 lists the identified system with 2024 ridership (unlinked passenger trips) and the year fares were removed from the system. The empirical analysis of this paper examines systems that removed fares after 2010 but before 2024, and excludes systems with 2010 ridership that was less than 500,000. The 14 systems that are used in the analysis are identified by bold text. I omit the non-bold systems in Table A1 from the pool of control systems.

Table A1: Transit Agencies Operating Fare-free

Agency	State	Ridership (2024)	Year Fares Removed
City of Commerce (CCT) - Transportation	CA	561,711	1962
City of East Chicago (ECT)	IN	53,129	1973
AppalCart (AC)	NC	1,516,410	1982
Island Transit	WA	496,782	1987
City of Wilsonville (SMART)	OR	197,607	1989
Cache Valley Transit District (CVTD)	UT	1,495,652	1992
Mason County Transportation Authority (MTA)	WA	532,336	1992
Indian River County (IRC)	FL	1,384,275	1995
City of Clemson (CAT)	SC	857,730	1996
Town of Chapel Hill	NC	3,885,139	2002
Regional Public Transportation Inc. (RPT)	ID	111,728	2004
City of Macomb (MCPT)	IL	413,649	2006
City of Marion (MTS)	IN	135,359	2008
City of Kokomo (COK)	IN	348,230	2010
City of Corvallis (CTS)	OR	1,020,099	2011
Missoula Urban Transportation District (MUTD)	MT	1,298,724	2015
Athens Transit (APT)	OH	321,163	2020
Chelan Douglas PTBA	WA	1,358,002	2020
City of Durham	NC	6,540,017	2020
City of Fairfax (CUE)	VA	1,002,134	2020
City of Fort Collins - Transfort	CO	2,651,954	2020
City of Tucson (COT)	AZ	17,970,113	2020
Grant County Transportation Authority (GTA)	WA	197,928	2020
Greater Richmond Transit Company (GRTC)	VA	10,990,419	2020
Intercity Transit (I.T.)	WA	4,589,073	2020
Kansas City Area Transportation Authority (KCATA)	MO	12,587,935	2020
Worcester Regional Transit Authority (WRTA)	MA	4,776,662	2020
City of Alexandria	VA	5,351,810	2021
Mississippi State University (SMART)	MS	430,049	2021
City of Rome (RTD)	GA	230,824	2022
County of Hawai'i*	HI	1,229,063	2022
Merrimack Valley Regional Transit Authority (MEVA)	MA	2,950,920	2022
Valley Transit (VT)	WA	502,014	2022
City of Albuquerque	NM	6,903,362	2024
Clallam Transit System (CTS)	WA	898,834	2024
Jefferson Transit (JTA)	WA	256,034	2024
Montgomery County, Maryland (MCDOT)	MD	18,434,535	2025

Full list of identified agencies operating fare-free in 2025. I report agency names as reported in the National Transit Database. *The County of Hawai'i system also operated fare free from 2005-2011.

B Synthetic Difference-in-Difference Estimation

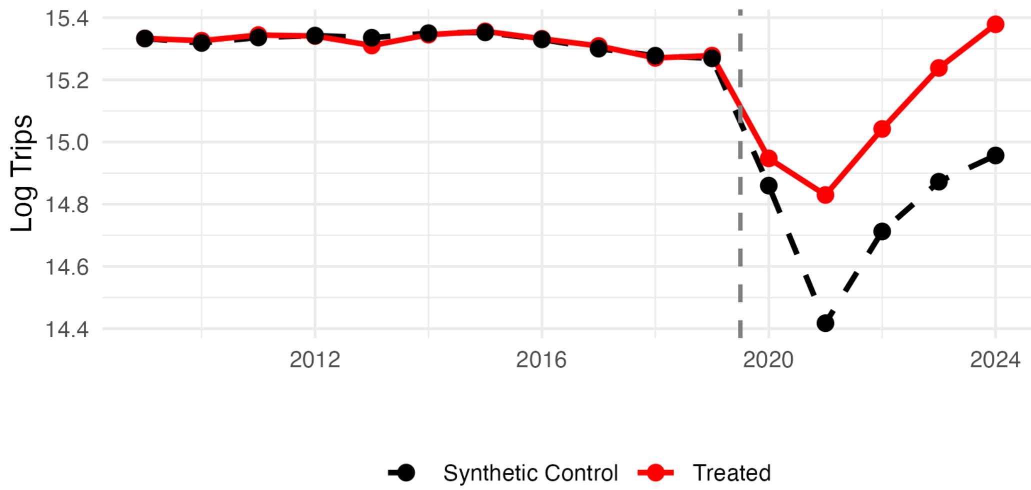
As a robustness check on this paper's main analysis, I also estimate main results under the *Synthetic Difference-in-difference* design proposed by Arkhangelsky et al. (2021). Because Synthetic Difference-in-difference is not well suited to an environment with staggered treatment, I limit this analysis to the nine agencies that adopted fare-free transit in 2020 and omit the other five treated agencies from the sample.

I first estimate the effect of fare elimination on ridership, measured as unlinked passenger trips. The main Synthetic Difference-in-difference estimate, which averages treatment effects across post-treatment years, is a 0.32 log point increase in ridership attributable to fare elimination, with a 95% confidence interval spanning 0.14-0.50. The result implies a 38% increase in trips, which is similar to the 46% estimated for the 14 treated systems using the staggered difference-in-difference methodology (Table 3, column 2).

Figure B1 presents results as an event study. The method is able to generate a closely fitting pre-trend by weighting the full set of available control agencies. I find a drop in ridership in both treated and control agencies due to the pandemic in 2020. However, the drop in ridership is significantly smaller for the nine agencies that adopted fare-free transit in 2020 and ridership remains significantly higher until the end of the study period. The final period of the event study indicates fare-free adoption increased ridership by 52%, similar to the 55% estimated in the staggered difference-in-difference method (Figure 6A). The estimates are not directly comparable because they use different treatment samples, but the alternative method confirms a large ridership treatment effect.

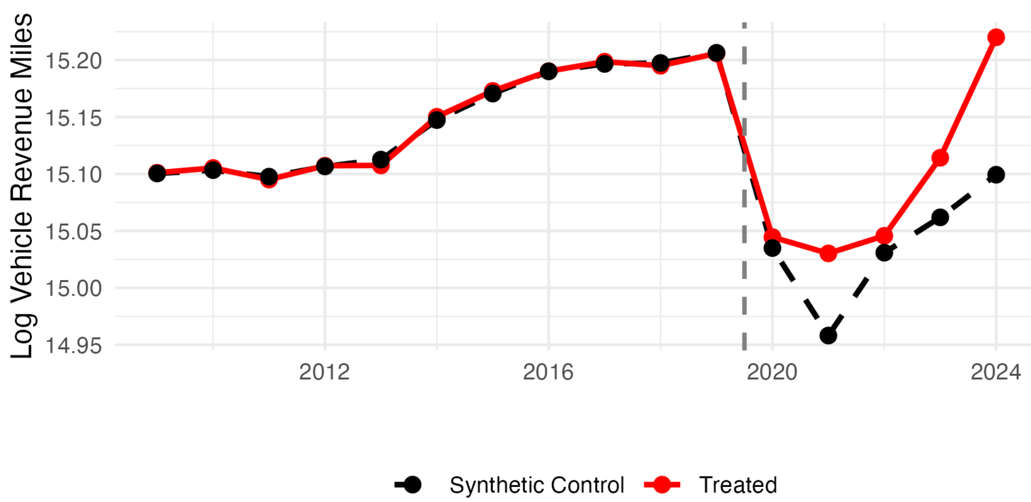
I also estimate the effect of fare elimination on level of service as measured by vehicle revenue miles. The model estimates a 5% (0.05 log point) increase in service, though the effect is not statistically significant. Figure B2 shows results as an event study. The final period result implies that fare elimination induced a 13% increase in vehicle revenue miles, relative to control agencies. The comparable full-sample, staggered difference-in-difference estimate was 14% (Figure 6B). The result confirms that fare-free systems tended to maintain higher service levels than control systems.

Figure B1: Synthetic Difference-in-Difference Event Study, Unlinked Passenger Trips



Treated observation include the nine systems that adopted fare-free programs in 2020.

Figure B2: Synthetic Difference-in-Difference Event Study, Vehicle Revenue Miles



Treated observation include the nine systems that adopted fare-free programs in 2020.