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

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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 16 US transit agencies that have recently eliminated fares. A staggered difference-in-differences analysis shows that fare elimination increased ridership by 49%, 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

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1 Introduction

Transit agencies periodically adjust fares, balancing fiscal pressures with accessibility and mobility goals. While completely eliminating fares has been uncommon 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 16 systems. On average, ridership increased by 49% following fare elimination. Agencies tended to expand service and investment despite the loss of revenue. I provide new evidence on the effects of fare-free public transit (FFPT) among agencies adopting the policy.

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 typically follow fare elimination.

Fare elimination schemes received relatively little academic study in the past (Keblowski, 2019), but have garnered more attention recently (Lightner et al., 2026; Štraub & Hess, 2025). European jurisdictions have hosted some significant fare-free systems. Luxembourg and Malta have both adopted free transit nationally. The cities of Tallinn, Estonia; Hasselt, Belgium; and Dunkirk, France have all had periods of FFPT. De Witte et al. (2006) broadly examines fare subsidies across Belgium, including fare-free programs, finding a positive ridership response. A national study of Poland identified 93 jurisdictions that provided some level of FFPT (Straub et al., 2023). FFPT adoption was spread across the country, occurred in both small and mid-sized cities and was more common in areas without significant support for far-right political parties. A German program that offered riders unlimited transit for a month for only €9 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 FFPT, 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, but 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]

FFPT has also been adopted widely in Brazil. Pereira et al. (2023) provides discussion on FFPT adoption for 15 Brazilian systems, finding adopting agencies tend to be small and are motivated by expanding mobility for marginalized groups. A recent analysis of FFPT in Brazil found that adoption led to both a rise in local employment and a reduction in local greenhouse gas emissions (Rodrigues et al., 2024).

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 FFPT 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 limitation, the authors find a significantly positive ridership effect. Estimates on labor force participation and local inequality metrics returned null results. Mendez (2025) took a case study approach by surveying riders in Kansas City after the local transit system became fare-free. Users reported significant mobility benefits, particularly those who were members of marginalized communities.

Partial FFPT programs, that target specific populations, are common in the US and have been well studied. Providing free transit to university students is a common policy across the US. Brown et al. (2001, 2003) provided analysis of these programs, finding student ridership 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.

Reduced transit vehicle dwell time is one possible advantage of removing fare payments. There is no empirical academic literature that has documented the effect. However, an internal study by the Massachusetts Bay Transportation Authority of its fare-free routes found dwell times fell by 6-23% (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).

FFPT 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

[1]See Hess (2017) for a detailed summary of research on FFPT in Tallinn.

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 evidence from system-wide fare elimination programs, which capture aggregate demand responses.

The results of this paper also relate to the literature estimating the elasticity of transit demand with respect to fares. Curtin (1968) provided early evidence that transit ridership responds inelastically to fare changes, with a commonly cited elasticity of approximately -0.3, implying modest ridership responses to marginal fare changes. Schimek (2015) generally confirmed this finding with more recent U.S. data but estimated stronger long-run responses. Analysis of riders in Sweden showed a slightly stronger elasticity of -0.46 (Kholodov et al., 2021). While these elasticity estimates are informative for predicting ridership changes from small fare adjustments, they are a poor guide for evaluating policies that eliminate fares entirely. Applying elasticities derived from marginal fare changes to a 100 percent fare reduction would require substantial out-of-sample extrapolation. Fare elimination entails the removal of transaction costs, which may independently affect ridership. In addition, the elasticity estimates would not account for other agency policy changes that typically accompany fare elimination.

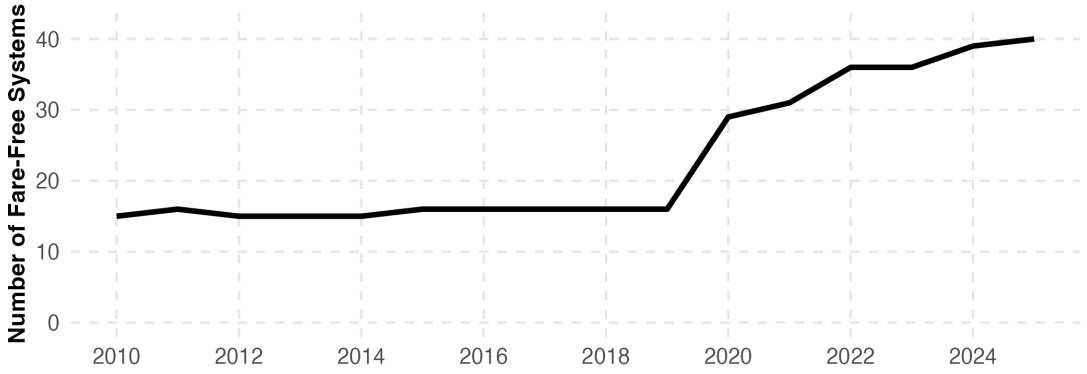
In contrast to RCTs and the elasticity literature, this study estimates the effects of full fare elimination on agencies that have actually implemented the policy, capturing both the direct demand response and the accompanying organizational adjustments. As a result, the estimates presented here should be interpreted as characterizing the typical experience of agencies that chose to eliminate fares, rather than the counterfactual effect of fare changes that would be expected for a randomly selected US transit agency. The estimates are directly relevant for agencies on the margin of implementing a fare-free policy.

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

2 The Expansion of Fare-free Public Transit in the US

The number of US transit systems operating entirely 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 40–a 150% 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 Public Transit Systems Over Time



Active fare-free systems by year (2010-2025) for agencies with 2010 ridership above 500,000. The figure is based on the full list of US FFPT systems as identified in Appendix A.

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

While there has been a recent uptick in FFPT adoption, several small US agencies have operated fare-free systems for decades. Commerce, CA has gone without fares since 1962 and East Chicago since 1973. Volinski (2012) provides a comprehensive discussion of the history of FFPT in the US context. Important demonstration projects of FFPT were completed in the late 1970s in Trenton, New Jersey and Denver, Colorado. Studenmund & Connor (1982) synthesized these experiments, finding net ridership increases of approximately 15% overall and around 45% during off-peak hours.

Targeted fare subsidies for specific groups such as university students, low-income riders, or seniors have long been common in the US (Boyd et al., 2003; Brough et al., 2022, 2025; Brown et al., 2001, 2003). This paper focuses exclusively on systems that are entirely fare-free.

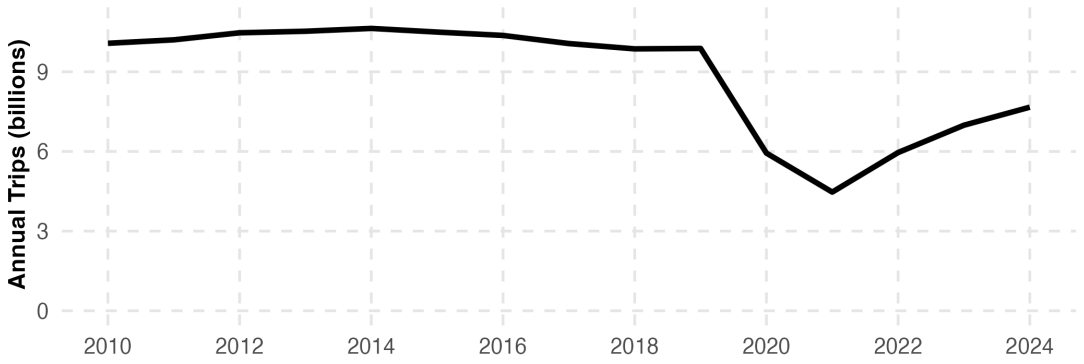
The COVID-19 pandemic, which triggered a steep decline in transit ridership across the country, was a major catalyst for the shift towards fare-free models. Many agencies responded to the pandemic by suspending fares, initially as a temporary measure (Maciejewska et al., 2025). Some of these agencies 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 rapid adoption of temporary FFPT measures in the US during the COVID-19 pandemic has been documented by Maciejewska et al. (2025) and Keblowski (2025). The former found that approximately two-thirds of urban transit agencies suspended fares temporarily, with adoption more likely in Democratic leaning areas. Keblowski (2025) further identifies prior institutional familiarity with FFPT and federal coronavirus relief funding as key enabling factors, with fare suspension justified primarily on grounds of physical distancing and financial relief for low-income riders.

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.

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.

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.

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 is 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.[3]

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).

Table 1: Transit Agency Panel Summary Statistics

	Mean	SD	Min	Max
Fare-free (dummy)	0.01	0.12	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.

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.

[3]Results are highly robust to dropping the largest systems. For example, main results are highly robust to removing the 10 largest US systems by ridership from the control group.

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 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.

The study period covers the pandemic era, which represented a significant shock to agency finances. Comparing 2019 to 2021, aggregate funding from State, Local, and "Other" sources fell by $0.7 billion, $5.5 billion, and $11.8 billion respectively across all NTD agencies. Federal funding more than doubled over the same period, increasing by $16.4 billion, driven largely by the Coronavirus Aid, Relief, and Economic Security (CARES) Act and the Coronavirus Response and Relief Supplemental Appropriations Act (CRRSAA) in 2020, as well as the American Rescue Plan (ARP) Act and the Infrastructure Investment and Jobs Act (IIJA) in 2021. As a result, total funding to US transit agencies fell only modestly during the pandemic, but underwent a significant shift in its composition toward federal sources. Because the majority of FFPT-adopting agencies in the empirical analysis eliminated fares during pandemic years, this unusual funding climate is important context for understanding how external funding enabled the shift to FFPT.

I manually construct a data set of FFPT 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 16 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.[4] Of these 16 agencies, 11 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 16 systems. Standard fares ranged

[4]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 16 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.

from $0.75 to $2.00. Table 2 lists the 16 fare-free agencies I identified.

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

Agency	Primary Municipality/County	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.	Richmond	VA	14,185,511	2020	$1.50
Intercity Transit	Olympia	WA	5,101,082	2020	$1.25
GoDurham	Durham	NC	5,059,368	2020	$1.00
DASH	Alexandria	VA	4,352,852	2021	$2.00
WRTA	Worcester	MA	3,493,141	2020	$2.00
Charlottesville Area Transit	Charlottesville	VA	2,195,455	2020	$0.75
Merrimack Valley RTA	Essex County	MA	2,132,657	2022	$1.25
Transfort	Fort Collins	CO	2,074,580	2020	$1.25
Athens-Clarke County Transit	Athens	GA	1,789,238	2020	$1.75
Hele-On	Hawai'i County	HI	1,301,603	2022	$2.00
Link Transit	Chelan & Douglas Counties	WA	1,029,155	2020	$1.00
CUE Bus	Fairfax	VA	929,897	2020	$1.75
Mountain Line	Missoula	MT	812,955	2015	$1.00
Corvallis Transit System	Corvallis	OR	700,820	2011	$0.75

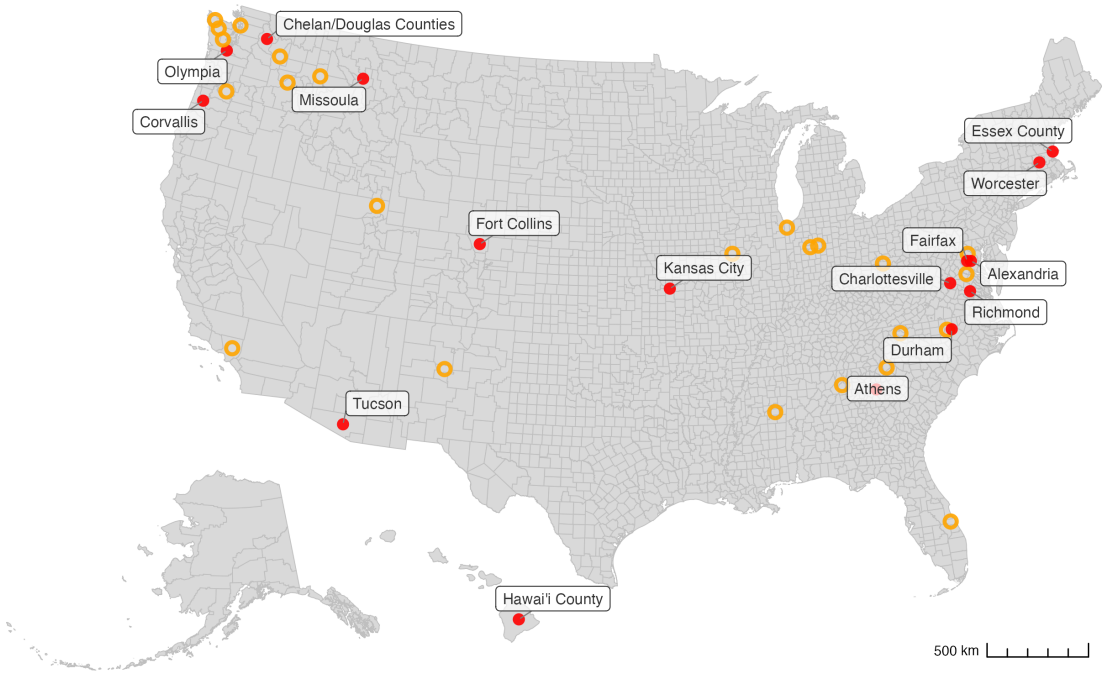
The 16 mid-sized agencies that adopted fare-free public transit within the study period.

Agencies adopting FFPT are spread out across the US. Figure 3 maps the location of the 16 treated agencies, as well as fare-free agencies who initiated fare-free policies outside of the study period. Four 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.

The multiple treated systems observed in Virginia and Massachusetts are a result of state level programs that funded fare-free transit. In Virginia, the Transit Ridership Incentive Program (TRIP) directly funded FFPT programs across the state, including the four systems included as treated agencies in the analysis. In 2022, Massachusetts voters adopted the Fair Share Amendment, which imposed a surtax on incomes above $1 million and earmarked a portion of revenue for transit. The state legislature then approved a $15 million fund specifically to fund fare-free transit systems, which benefited the two treated Massachusetts agencies.

While none of the nation's largest transit systems have removed fares, FFPT was adopted across a range of agency sizes. Figure 4 provides the distribution of logged 2010 unlinked passenger trip counts across all 407 agencies in the sample, with the

Figure 3: Location of Fare-Free Systems

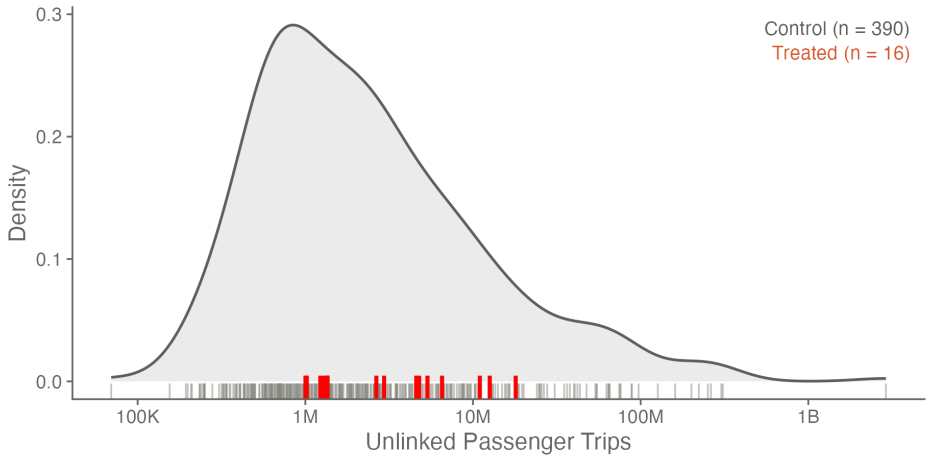


Fare-free systems operating in the US in 2024 are shown. Treated systems are limited to those with 2010 ridership of at least 500,000 and that eliminated fares during the study period. The full list of fare-free systems is provided in Appendix Table A1. County boundaries are shown.

16 fare-free (treated) agencies marked by red indicators along the x-axis. The treated agencies are concentrated in the small-to-mid range of the distribution. The largest system to remove fares was Sun Tran in Tucson, AZ, recording 21 million trips in 2010, which is at the 87th percentile of the study sample. Several treated agencies fall near the lower end of the distribution, around 1 million annual trips.

Prior literature has suggested that FFPT 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. The metric represents the number of transit boardings per mile of vehicle operation and averages 1.49. Figure 5 shows the distribution of system utilization across all 407 sys-

Figure 4: Sample Distribution of Unlinked Passenger Trips, Log Scaled



: Marks location of fare-free (treated) agency in distribution

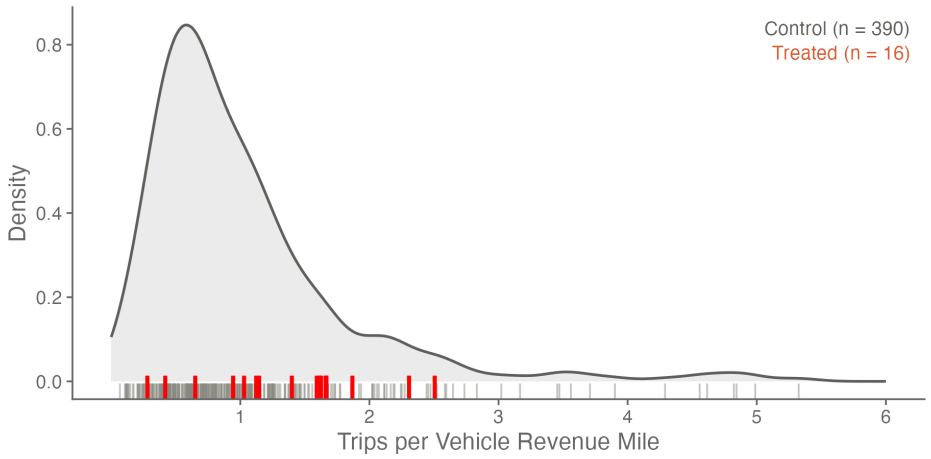
Unlinked passenger trips is equal to the number of transit vehicle boardings in a year. I include only agencies with ridership of at least 500,000 in 2010. Trips are logged in the figure. Red lines on the x-axis indicate the 16 agencies that adopted FFPT during the study period and grey lines represent all other agencies. N = 407.

tems in the sample, with the 16 treated agencies marked by red indicators. The treated agencies cover a wide range of utilization levels, demonstrating that treatment status is not specific to low-utilization systems.

While the 16 treated agencies all introduced FFPT, they differed significantly in their program roll-out, funding sources, motivation for implementation, and other details. Table 3 summarizes the specific experiences of the 16 systems to provide additional agency-specific context. Results of the analysis do show some heterogeneity in outcomes across systems, which may be related to differences in how FFPT was implemented.

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 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

Figure 5: Sample Distribution of Utilization, Trips per Vehicle Revenue Mile



▌: Marks location of fare-free (treated) agency in distribution

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 lines on the x-axis indicate the 16 agencies that adopted FFPT during the study period and grey lines represent all other agencies. N = 407. Eight observations exceed six trips per vehicle revenue mile and are not shown.

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-differences 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-differences 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

Table 3: Details on Treated Fare-free Systems

Agency	Fare-free Timeline	Notes on Unique Financing Sources	Other Notes
Sun Tran	Launched March 21, 2020.	Initial funding from CARES Act. Money from a local hotel tax has been directed to the fare-free program.	The Tucson City Council voted repeatedly to extend the fare-free policy, but have noted the need to find sustainable funding sources.
RideKC	Launched March 19, 2020. Fares reinstated June 1, 2026.	Initial funding from CARES Act. Kansas City imposes a local sales tax to fund transit.	Kansas City Council voted in 2019 to remove fares in the future but the implementation date was moved forward as a pandemic response. The KC Streetcar will remain fare-free after fares are reintroduced in 2026.
Greater Richmond Transit Co.	Launched March 19, 2020. Extended to July 31, 2026.	The program received $8 million through Virginia's TRIP funds. Additional funds have been provided through the federal IIJA and a contribution from Virginia Commonwealth University.	The agency has called for future funding to be secured through expanded private donations and increased advertising revenue.
Intercity Transit	Launched January 1, 2020. Extended to 2028.	A 2018 ballot measure (Proposition 1) instituted a 0.4% local sales tax to fund transit expansion and fare removal.	Although FFPT began in 2020, the decision and implementation predates the COVID-19 pandemic.
GoDurham	Launched March 23, 2020. Extended to June, 2026.	Supported by federal pandemic relief funds.	The surrounding regional transit operator (GoTriangle), which has lower ridership, also went fare-free as a COVID response, but restored fares in 2024.
DASH	Launched September 5, 2021.	The program received a $7.2 million grant through Virginia's TRIP funds.	DASH also removed fares as a temporary COVID response from March 2020 to March 2021. The removal of fares was accompanied by a significant redesign of the bus system, expanding routes and launching 24-hour service.
WRTA	Launched March, 2020. Extended to June, 2026.	Initial funding from CARES Act. Received a $2 million grant resulting from the Massachusetts Fair Share Amendment in 2024.	The fare-free policy has been continued through a series of short-term extensions.
Charlottesville Area Transit	Launched March 18, 2020.	The program received a $1 million grant through Virginia's TRIP funds.	One major bus line already provided fare-free service prior to 2020. Concurrent with fare elimination, the agency eliminated Sunday service.
Merrimack Valley RTA	Launched March 1, 2022. In 2025, the system adopted a permanent fare-free policy.	Partially funded by revenue from the Massachusetts Fair Share Amendment.	In 2019, three lines ran fare-free as part of a two-year demonstration project.
Transfort	Launched March, 2020. In 2024, the agency adopted a permanent fare-free policy.	Beginning in 2023, a local sales tax was introduced to partially fund transit.	An internal report found that restoring fares would cover less than 3% of the agency budget. Currently implementing a system expansion plan.
Athens-Clarke County Transit	Launched March 18, 2020.	Initial funding from CARES Act. In 2023, voters approved the 1% Transportation Special Purpose Local Option Sales Tax to support transit.	Children already rode free prior to the policy change. The removal of fares coincided with service reductions. The agency was subsequently unable to expand service, with agency officials pointing to a bus driver shortage as the cause.
Hele-On	Launched June 3, 2022. Extended to 2028.	The recent fare-free period is funded through a $4.5 million CRRSAA grant and a $1.9 million ARP Act grant.	Operated fare-free from 2005-2011 before charging fares until 2022. New federal grants greatly exceeded previous fare box revenue, allowing for system expansion as well as fare removal.
Link Transit	Launched March 20, 2020.	The agency is supported by a 0.5% local sales tax. The Move Ahead Washington program also partially funds operations.	From establishment (1991) until 2000, the agency was fare-free. From 2000 until 2020 fares were collected. Three bus routes were already fare-free when the COVID policy was enacted.
CUE Bus	Launched in March, 2020. Extended as a four-year program, running from 2022-2026.	The four-year program was funded through ARP Act funds and through Virginia's TRIP funds ($651,000). George Mason University (GMU) provides annual financial contributions of $750,000 through a partnership.	GMU represents a primary node of the bus network.
Mountain Line	Launched January 5, 2015.	In 2020, voters approved a property tax increase to permanently fund FFPT.	The program was originally implemented as a three-year demonstration project, but subsequently extended.
Corvallis Transit System	Launched February 1, 2011.	Permanently funded through a fee assessed on all local utility payers.	Oregon State University represents a primary node of the bus network.

Details on FFPT implementation were collected from agency websites, press releases and news reports.

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-differences setups with staggered treatment requires an adjustment to the estimator (Goodman-Bacon, 2021; Callaway & Sant'Anna, 2021). I adopt the staggered difference-in-differences estimator proposed in Callaway & Sant'Anna (2021), which is not subject to the bias identified in Goodman-Bacon (2021).

The staggered difference-in-differences 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 effect of the policy, I also estimate how 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 valid control group 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 16 systems I study, comparing ridership the year before fare elimination to ridership one year following free-fare adoptions shows that the average system saw only a 0.5% increase in ridership. However, this estimate is significantly impacted by the contaminating effect of the pandemic.

The methodology identifies average treatment effects for agencies that chose to eliminate fares by comparing changes in outcomes among adopting agencies relative to non-adopting agencies. By demonstrating parallel pre-treatment trends, I provide evidence that outcomes change systematically following fare removal in ways that cannot be explained by observable pre-existing difference of adopting agencies, nor from nation-wide changes over time. However, the resulting estimates should not be inter-

preted as the effect expected for the average US transit system, but rather as effects specific to agencies that chose to remove fares. Such agencies may have done so in conjunction with broader organizational changes, shifts in local political priorities, or advance knowledge that new funding sources would become available. Increased ridership following fare removal could itself raise grant allocations, since ridership is often an input in grant formulas. To the extent that such concurrent changes simultaneously affected outcomes, the estimates reflect the combined effect of fare elimination and its accompanying factors rather than the isolated causal effect of fare removal alone. Put another way, I estimate the average treatment effect on the treated (ATT) rather than an average treatment effect (ATE), and the results are best understood as describing the typical experience of agencies that adopted fare-free service.

To identify agency specific effects, I subsequently estimate a synthetic control model, which I apply to each of the 16 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-differences* approach outlined in Arkhangelsky et al. (2021). The method combines a difference-in-differences 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-differences design to estimate the consequence of fare-removal 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 16 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-differences Results

Table 4 presents the main results of the Equation 1 staggered difference-in-differences specification. Column 1 shows the estimated change in unlinked passenger trips for agencies adopting FFPT. I estimate that fare elimination is related to a 42% increase in trips for the average treated system. The effect is highly statistically significant. Plausibly, the impact of ridership changes associated 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 is unchanged at 42%. The stability of the estimate suggests the result is driven by a demand response and not driven by local COVID-19 prevalence or endogenous changes in the agency's level of service.

The staggered difference-in-differences 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.[5] In post-treatment years one, two, three and four, I find ridership

[5]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. The main result (Table 4, column 3) is also robust to dropping 2020

Table 4: 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	0.351**	0.350**	0.351**	0.084*	0.091*	0.091*
	(0.072)	(0.073)	(0.072)	(0.037)	(0.036)	(0.037)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Agency fixed effects	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.

is increased by 36%, 41%, 42% and 49% 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. I take 49% to be the long-run impact of fare elimination on ridership.

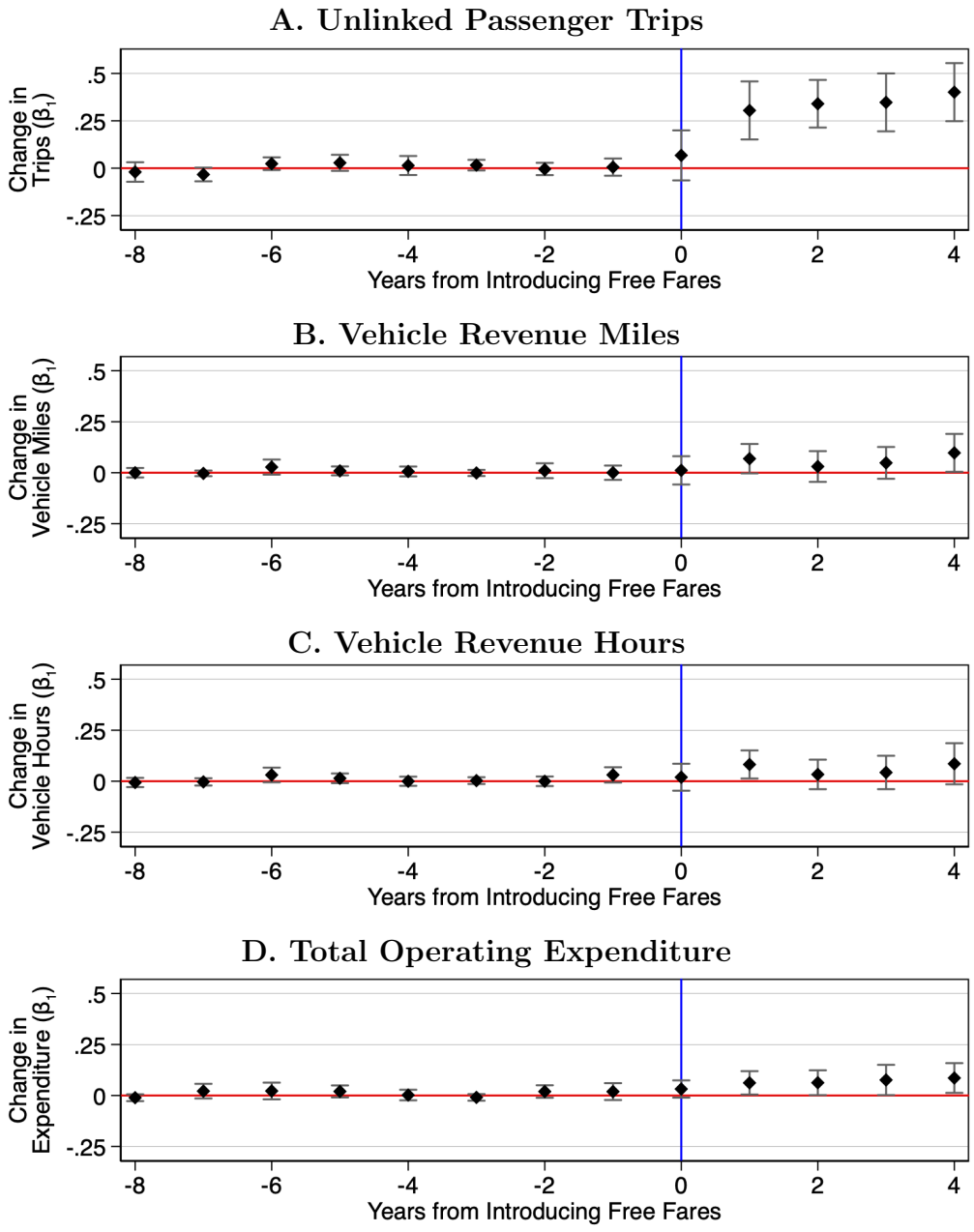
The estimates rely on a larger sample of fare-free agencies and cover a longer post-treatment time period than prior studies in the literature. The estimated ridership effect is nearly double the effect estimated in Ofosu-Kwabe et al. (2024), who estimated a 28% ridership increase in medium sized US markets and 34% in smaller markets. The estimates are significantly larger than those evaluating fare elimination in Tallinn (Cats et al., 2014, 2017). While the effects of full fare elimination might be inherently different than marginal fare changes, the main estimate (Table 4, Column 3) implies an elasticity of -0.42, which is in line with recent estimates of fare elasticities (Schimek, 2015; Kholodov et al., 2021).

I do not observe trip characteristics, for example trip length. While I find a large increase in the total number of trips, it is likely that the marginal trips that occurred because of fare elimination were shorter, lower-value trips relative to trips where people have a willingness to pay that exceeds the initial fare level. In the context of Tallinn, Cats et al. (2014) showed that average trip length fell by 11% after fares were removed.

I use the same difference-in-differences methodology to evaluate the impact of fare

and 2021 observations completely, which generates an increased estimate of 0.557, significant at the 1% level.

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



Results of the staggered difference-in-differences 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.

elimination on level of transit service. Table 4 columns 4-6 present level of service results. Column 4 estimates the change in vehicle revenue miles following fare elimination. I estimate a significant 8.8% increase in vehicle revenue miles. For vehicle revenue hours I estimate a statistically significant 9.5% 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 9.6% expenditure increase. Overall, I find evidence that the agencies that removed fares subsequently 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. The ability of agencies to access funding, may have been aided by the period of generous federal spending that coincided with the pandemic recovery. I provide evidence for funding mechanisms 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 higher in treated agencies than control agencies, with vehicle revenue miles and total operating expenditure statistically significantly higher. 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 5 estimates the staggered difference-in-differences 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 is followed by a positive 3.7% 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 tying 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 45% for the average treated agency after fare elimination (column 4). I find a large and significant 78% 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 5: Impact of Free Transit on Log of Agency Funding

	Total	Federal	State	Local	Other	Operating	Capital
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fare-free System	0.036	0.226	0.538	0.371*	-1.536**	0.084**	-0.240
	(0.065)	(0.429)	(0.687)	(0.183)	(0.528)	(0.032)	(0.558)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agency fixed effects	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 a clear identification of 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 a 71% increase, on average. Overall, the results suggest the average agency is able to expand government transfers after eliminating fares, though experiences differ considerably across agencies as to what source of external funding is tapped.

Table 5 columns 6-7 break out funding received by money devoted to operating versus capital expenditures. I find that funding devoted to operating expenses increased by a significant 8.7%, while I find a statistically insignificant effect on capital project funding. An increase in operating expenses is consistent with service expansion after fare elimination.

5.2 Synthetic Control Method Results

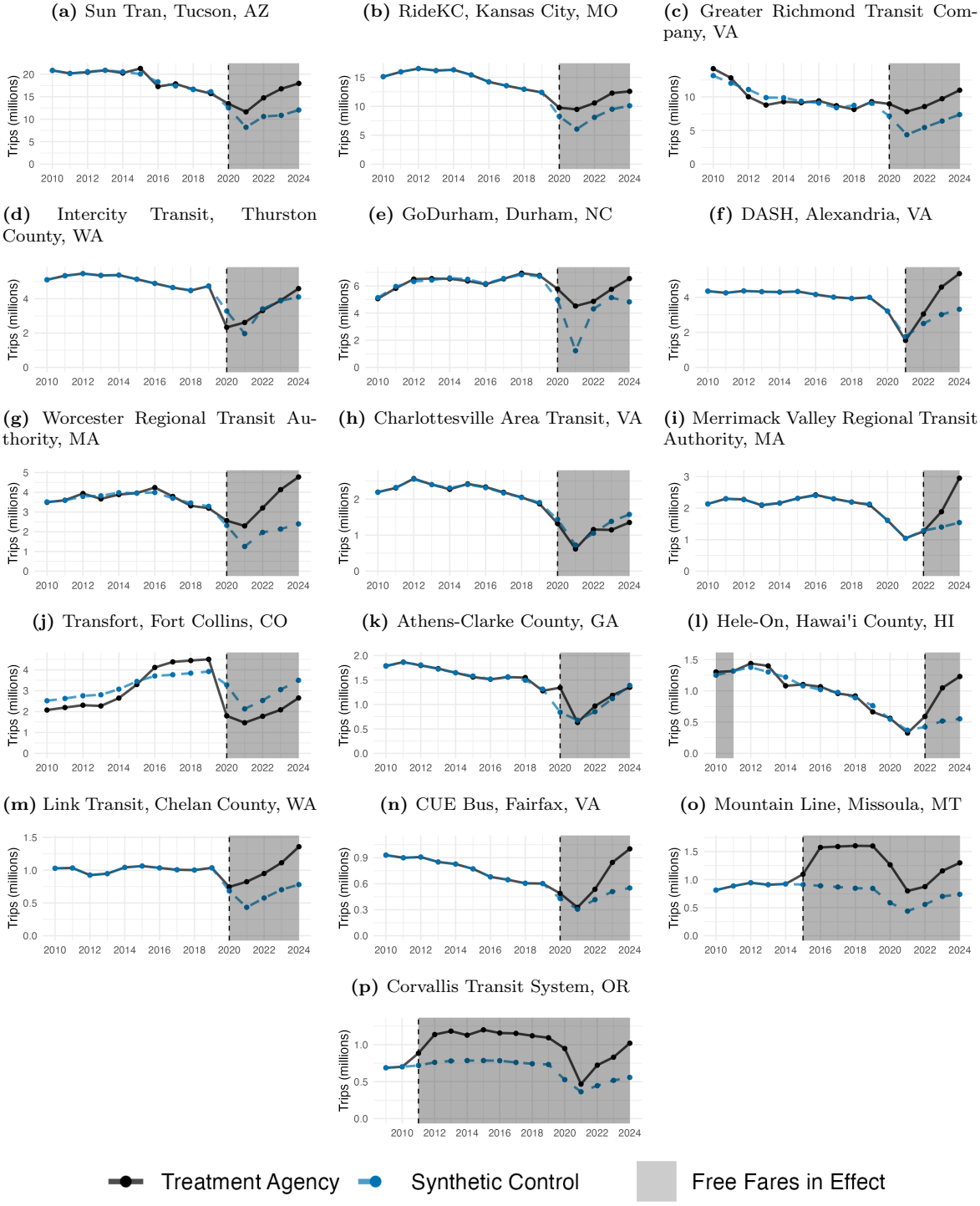
The previous section establishes that fare elimination is correlated with large ridership gains and a significant increase in an agency's level of service, on average. I now apply a synthetic control method to yield agency specific estimates. Some prior research on fare-free systems suggests benefits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

Figure 7 displays estimates of ridership changes from fare elimination for all 16 systems based on the synthetic control method.[6] For 13 of 16 systems, I estimate an increase in ridership. I find the average system experienced 51% growth in ridership due to fare elimination, with the median estimated as 55%. These estimates are slightly larger but consistent with the 49% increase estimated under the staggered difference-in-differences 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 16 systems. Figure 8 provides the estimated change in vehicle revenue miles that typically follows fare elimination. I estimate vehicle revenue miles increased in seven of 16 systems. However, agencies that did increase service tended to increase it substantially. Across all agencies, the average change was a 11.9% 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

[6] 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.

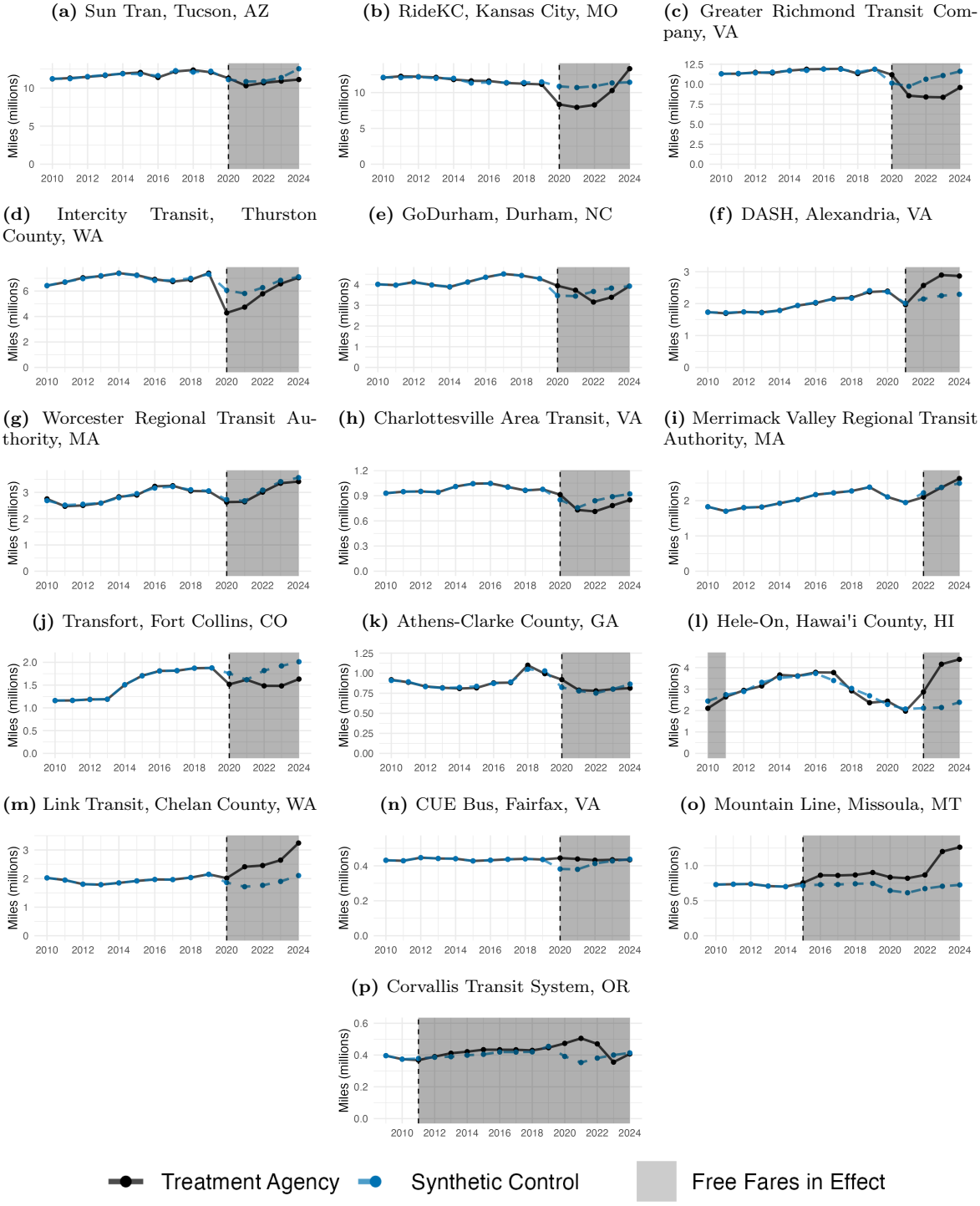
Transit System (Oregon) had a level of service that was roughly the same as control agencies. These different experiences highlight the idiosyncrasy in how service level relates to fare elimination. Across the 16 systems, estimated changes in service level ranged from -18.9% (Transfort, Fort Collins, 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-differences and synthetic control methods. In Appendix B, I provide additional results for ridership and service level changes from a synthetic difference-in-differences 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. While the direction of the effect is consistent with this mechanism, 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 32 percentage point larger increase in ridership. However, due to the small sample size, this effect is also statistically insignificant.

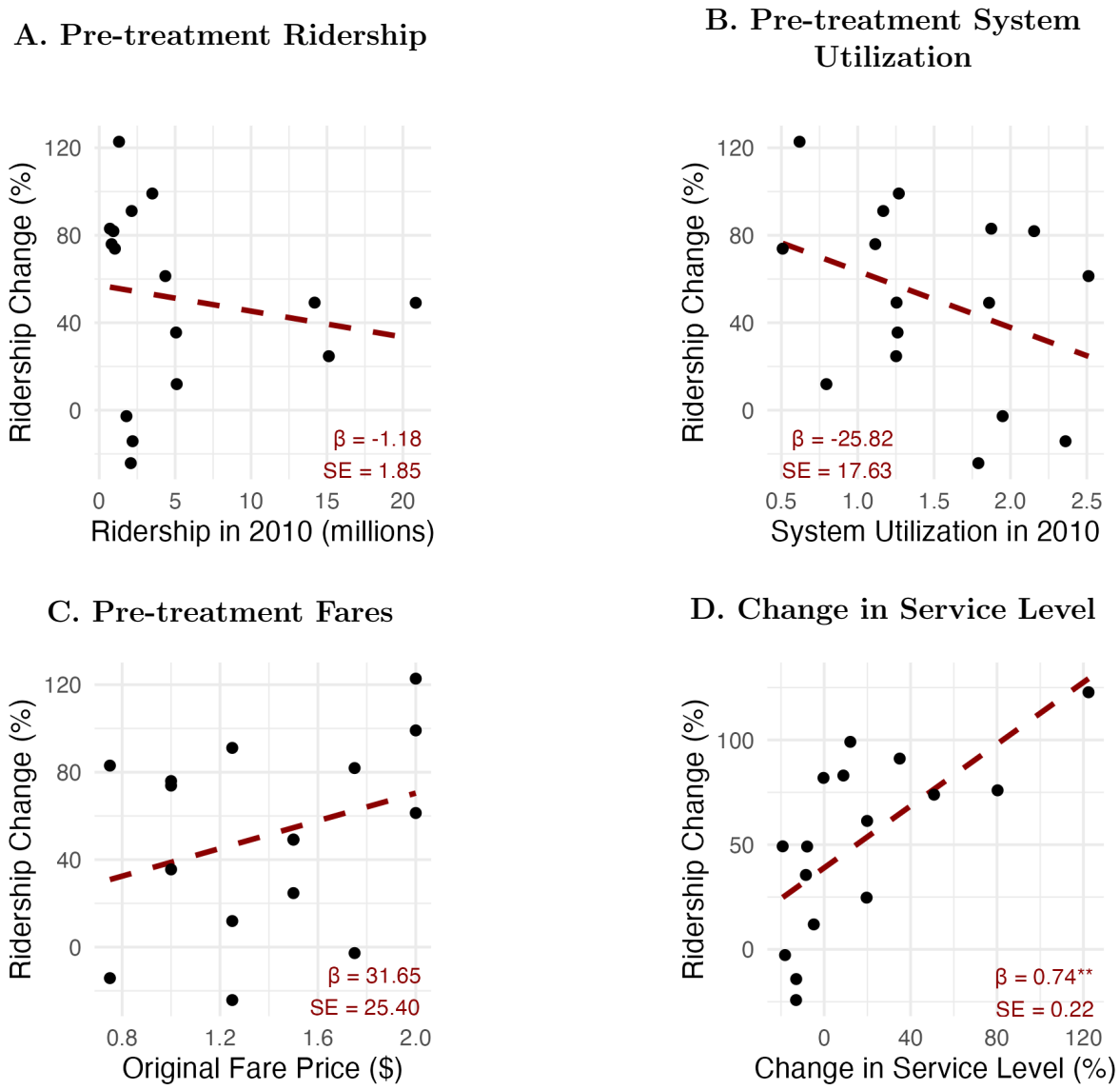
Finally, Panel D investigates the relationship between service level changes and the effect of fare removal. Service level is proxied by the percent change in vehicle revenue miles between the year before fare elimination and the final year of observation. Here, I find significant evidence that agencies reducing service at the same time as implementing fare-free policies saw smaller ridership gains. Specifically, a 10% cut in

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.

service is associated with a statistically significant 7.4 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 seven agencies that cut service all experienced among the smallest ridership gains.

The three systems where fare elimination coincided with reduced ridership (Transfort, Fort Collins, CO; Charlottesville Area Transit, VA; and Athens-Clarke County Transit, GA) all cut service by more than 10%. Charlottesville entirely eliminated Sunday service when fares were removed. Transfort had charged $1 fares prior to fare elimination while Charlottesville charged only $0.75. Athens-Clarke County had already provided fare-free service to those under 18. These specific agency conditions likely also contributed to the policy change being 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-differences analysis I estimate fare elimination triggers a ridership increase of 42%, when averaged across post-treatment years (Table 4). 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 FFPT programs in the US. However, my sample includes only 16 adopting systems, which limits statistical power in the analysis. While these 16 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.

The high-level analysis of this paper is intended to complement case study work that provides a fuller context regarding the experience of specific agencies (e.g. Cats et al. (2017); Mendez (2025)). While I provide some agency-specific results through the synthetic control method, each FFPT adopting agency has a unique institutional history, funding context, and set of accompanying policy changes that aggregate analysis cannot fully capture. For example, the details of concurrent service expansions, state-level financial incentives, or prior partial fare-free programs may all shape the ridership and financial outcomes observed for individual systems. Fuller case study evidence would provide important context for understanding how FFPT has functioned on the ground, and for explaining the heterogeneity in outcomes documented here.

6 Discussion and Conclusions

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 49%. 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 16% 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). Inducing greater ridership through fare elimination may itself lead to more funding. In an interview about FFPT, the manager of Hawai'i County's Hele-On bus system noted, "Higher ridership translates into increased Federal and State formula

funding and creates a positive feedback loop."[7]

Compared to prior literature (Studenmund & Connor, 1982; Cats et al., 2017; Ofosu-Kwabe et al., 2024), I find a large (49%) ridership increase among treated agencies, with 13 of 16 systems showing positive ridership effects. The magnitude of the ridership increase is an important parameter for agencies contemplating FFPT, as systems will need to plan for substantially higher passenger volumes following fare elimination. The findings on service level and financing are novel contributions of this study. A common concern among agencies considering FFPT is that lost fare revenue will create funding deficits requiring service cuts. Current US experience provides no evidence of this. Future work should nonetheless examine the longer-run impacts of FFPT, which fall outside the timeframe analyzed here.

Agencies considering FFPT can draw lessons from the experiences documented in this study. Access to new funding sources, whether through federal grants, state programs, or local mechanisms such as sales or property tax measures, appears to be a common feature of successful FFPT adoptions. For FFPT to produce positive outcomes for riders, the decision to eliminate fares needs to be made in conjunction with a realistic plan for increasing revenue. The evidence suggests that this is indeed what tends to happen in practice, with agencies making coordinated decisions about fares, service levels, and financing.

In recent years, fully fare-free policies have become more common in the US. Beyond the agencies studied above, additional agencies have recently enacted local ordinances to initiate fare-free service going forward. 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. On the other hand, *RideKC* (Kansas City) reintroduced fares in 2026 after a six-year fare-free period. Changing policies around fare-free programs offer valuable opportunities for continued policy research, with the potential to deepen our understanding of FFPT's impacts on mobility, equity, and broader societal outcomes.

[7] John Andoh, Hawai'i County Mass Transit Administrator and General Manager, quoted in "Hawai'i Island Bus System Will Be Free Through at Least 2023," Hawai'i Public Radio, June 7, 2022, https://www.hawaiipublicradio.org/local-news/2022-06-07/hawaii-island-bus-system-will-be-free-through-at-least-2023.

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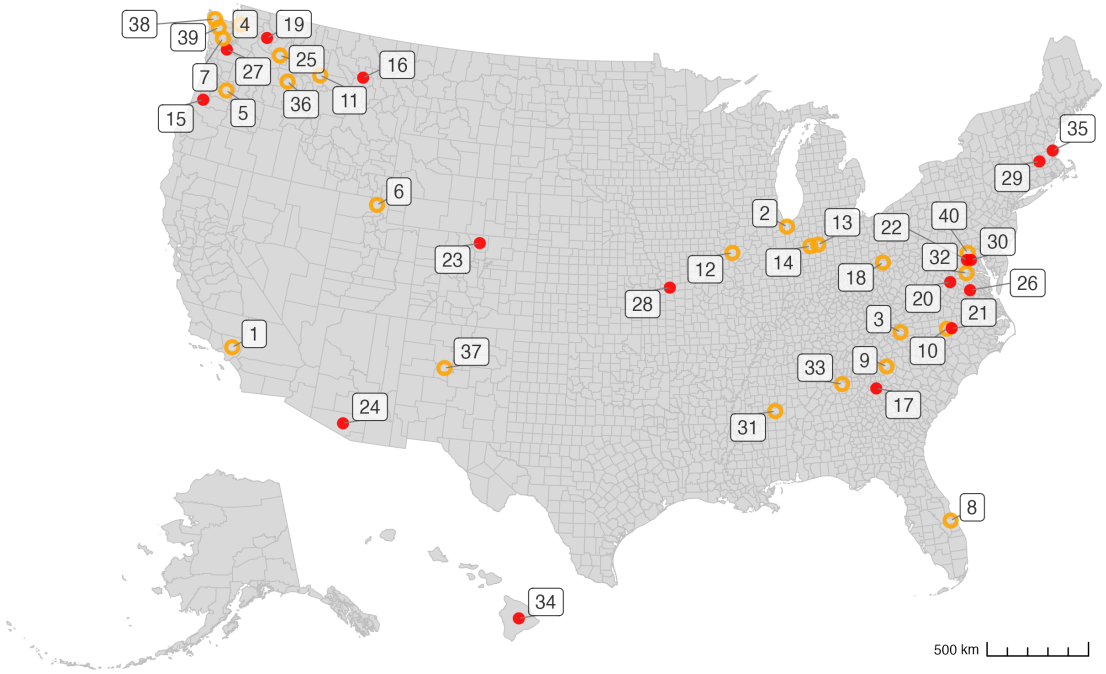
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A Fare-free Systems

Through searches of public reports and documents I identify 40 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 16 systems that are used in the analysis are identified by bold text. I omit the non-bold systems in Table A1, that operated fare-free during the study period, from the pool of control systems. The location of all 40 systems are mapped in Figure A1, with numbers indexed in Table A1.

Figure A1: Location of Fare-Free Systems



● Treated fare-free system ○ Other fare-free system

Fare-free systems operating in the US in 2024 are shown. The label numbers correspond to those provided in Table A1. County boundaries are shown.

Table A1: Transit Agencies Operating Fare-Free

	Agency	State	Ridership (2024)	Year Fares Removed
1	City of Commerce (CCT) - Transportation	CA	561,711	1962
2	City of East Chicago (ECT)	IN	53,129	1973
3	AppalCart (AC)	NC	1,516,410	1982
4	Island Transit	WA	496,782	1987
5	City of Wilsonville (SMART)	OR	197,607	1989
6	Cache Valley Transit District (CVTD)	UT	1,495,652	1992
7	Mason County Transportation Authority (MTA)	WA	532,336	1992
8	Indian River County (IRC)	FL	1,384,275	1995
9	City of Clemson (CAT)	SC	857,730	1996
10	Town of Chapel Hill	NC	3,885,139	2002
11	Regional Public Transportation Inc. (RPT)	ID	111,728	2004
12	City of Macomb (MCPT)	IL	413,649	2006
13	City of Marion (MTS)	IN	135,359	2008
14	City of Kokomo (COK)	IN	348,230	2010
15	**City of Corvallis (CTS)**	OR	1,020,099	2011
16	**Missoula Urban Transportation District (MUTD)**	MT	1,298,724	2015
17	**Athens-Clarke County Transit (ACCTD)**	GA	1,348,475	2020
18	Athens Transit (APT)	OH	321,163	2020
19	**Chelan Douglas PTBA**	WA	1,358,002	2020
20	**City of Charlottesville (CAT)**	VA	1,353,061	2020
21	**City of Durham**	NC	6,540,017	2020
22	**City of Fairfax (CUE)**	VA	1,002,134	2020
23	**City of Fort Collins - Transfort**	CO	2,651,954	2020
24	**City of Tucson (COT)**	AZ	17,970,113	2020
25	Grant County Transportation Authority (GTA)	WA	197,928	2020
26	**Greater Richmond Transit Company (GRTC)**	VA	10,990,419	2020
27	**Intercity Transit (IT)**	WA	4,589,073	2020
28	**Kansas City Area Transportation Authority (KCATA)**	MO	12,587,935	2020
29	**Worcester Regional Transit Authority (WRTA)**	MA	4,776,662	2020
30	**City of Alexandria**	VA	5,351,810	2021
31	Mississippi State University (SMART)	MS	430,049	2021
32	City of Fredericksburg (FRED)	VA	332,441	2022
33	City of Rome (RTD)	GA	230,824	2022
34	**County of Hawai'i***	HI	1,229,063	2022
35	**Merrimack Valley Regional Transit Authority (MEVA)**	MA	2,950,920	2022
36	Valley Transit (VT)	WA	502,014	2022
37	City of Albuquerque	NM	6,903,362	2024
38	Clallam Transit System (CTS)	WA	898,834	2024
39	Jefferson Transit (JTA)	WA	256,034	2024
40	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-Differences Estimation

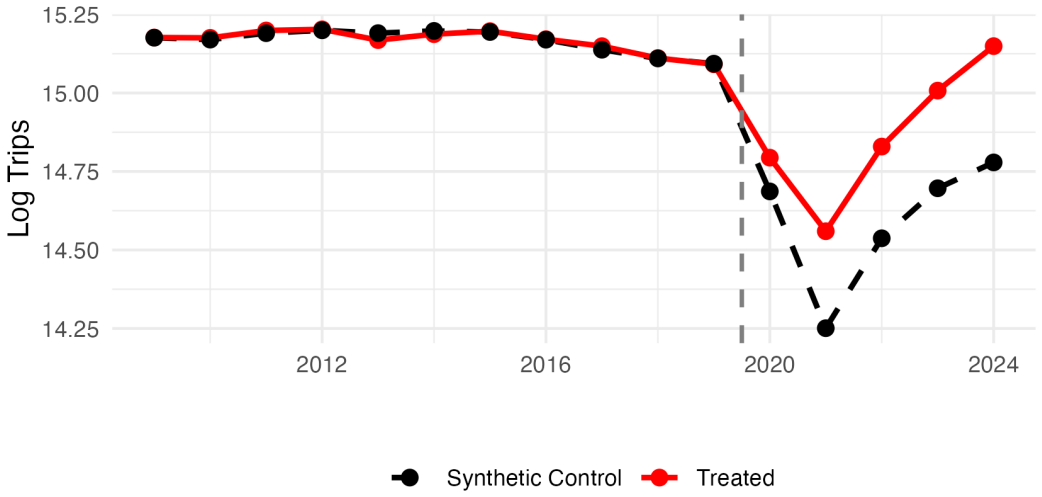
As a robustness check on this paper's main analysis, I also estimate main results under the synthetic difference-in-differences design proposed by Arkhangelsky et al. (2021). Because synthetic difference-in-differences is not well suited to an environment with staggered treatment, I limit this analysis to the 11 agencies that adopted FFPT 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-differences estimate, which averages treatment effects across post-treatment years, is a 0.28 log point increase in ridership attributable to fare elimination, with a 95% confidence interval spanning 0.12-0.44. The result implies a 32% increase in trips, which is similar to the 42% estimated for the 16 treated systems using the staggered difference-in-differences methodology (Table 4, 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 11 agencies that adopted FFPT 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 45%, similar to the 49% estimated in the staggered difference-in-differences 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.

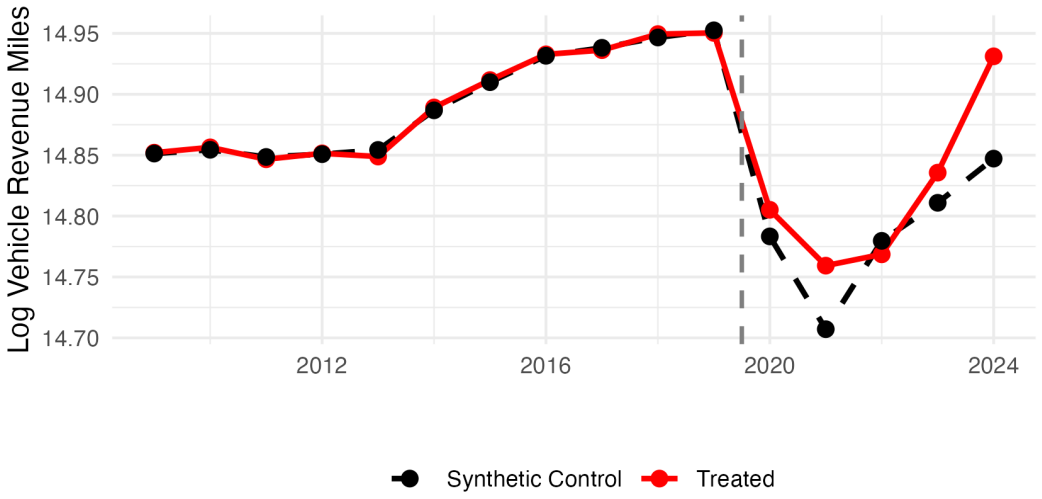
I also estimate the relationship between fare elimination and level of service as measured by vehicle revenue miles. The model estimates a 4% (0.04 log point) increase in service, though the effect is not statistically significant. Figure B2 shows results as an event study. The final period result implies that fare elimination correlates with a 9% increase in vehicle revenue miles, relative to control agencies. The comparable full-sample, staggered difference-in-differences estimate was 10% (Figure 6B). The result confirms that fare-free systems tended to maintain higher service levels than control systems.

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



Treated observations include the ten systems that adopted fare-free programs in 2020.

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



Treated observations include the 11 systems that adopted fare-free programs in 2020.