Does *Uber* reduce public transit ridership? Evidence & impacts in the San Francisco Bay Area

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Abstract

Many public transit authorities believe ride-hailing reduces ridership, thus hurts transit solvency. If so, municipalities may also face increased congestion and pollution. We develop methods measuring metro-specific, hourly impacts. Our estimates use a decade of route-by-hour data from the San Francisco Bay Area transit. We employ difference-in-differences with weather and traffic as route-specific exogenous, hourly shocks, which we interact with ride-hailing availability and find large short-run decreases in transit ridership. Then, comparing ridership trends, before and after ride-hailing begins, we find long-run year-over-year losses of over 10 percent. Fare revenue loss and social cost are *each* around $100 million in 2013, growing to $200 million in 2018.

Keywords: Public transportation; Ride-hailing; Disruptive technology; First/last mile; Externalities of driving.

JEL Codes: R40; H42; O33; Q51

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1 Introduction

Uber Technologies Inc. created the first widely available, ride-hailing app to improve taxi-like services. The emergence of its competitor, *Lyft*, solidified this new transportation mode in the market place. Established in March 2009 and June 2012, respectively, these ride-hailing companies are powerful forces altering consumer transportation.[1] Ride-hailing companies undercut the taxi industry, which is struggling to adapt to the direct competition and convenience (Berger et al., 2018; Cramer and Krueger, 2016; Wallsten, 2015). Many public transit authorities worry about negative impacts on their ridership demand. According to anecdotes and some regional studies, *Uber* and *Lyft* entice passengers away from public transit (Clewlow, 2019).[2] However, others argue that ride-hailing increases the value of public transit and encourages ridership — by chauffeuring passengers into public-transit service areas, which are geographically-limited, and by providing on-demand availability in harmony with the time-tables of public transit (Feigon and Murphy, 2016; Rayle et al., 2016). To answer how ride-hailing affects transit ridership, we develop methods for measuring metro-specific, hourly and daily impacts.

The emerging group of empirical studies disagree whether and to what extent *Uber* and *Lyft* compete against versus complement public transportation. Hall et al. (2018) provide an important starting point. Using the variation in *Uber*X entry across US cities, they estimate a difference-of-differences model of monthly regional public-transit ridership. By analyzing the two years of data after *Uber*X market entry, they find a complementary relationship on average: public transit increases by 5 percent. However, their results differ by city-type: those with above median ridership show a decline in ridership, whereas cities with above median population increase ridership — indicating an ambiguous result for places like San Francisco. Babar and Burtch (2017) use a similar approach and include other covariates to explain additional aspects of the relationship, but they also find complementarity. However, Nelson and Sadowsky (2018) use regression discontinuity to show that, when *Uber*X first enters, the ride-hailing company complements public transit, but after *Lyft* enters the

[1] These companies, often called Transportation Network Companies (TNCs), offer an internet-based mobile-phone app that links a person seeking transportation and a driver. In most municipal areas, the driver arrives at the consumer's exact location within minutes and provides a ride to a specific destination.

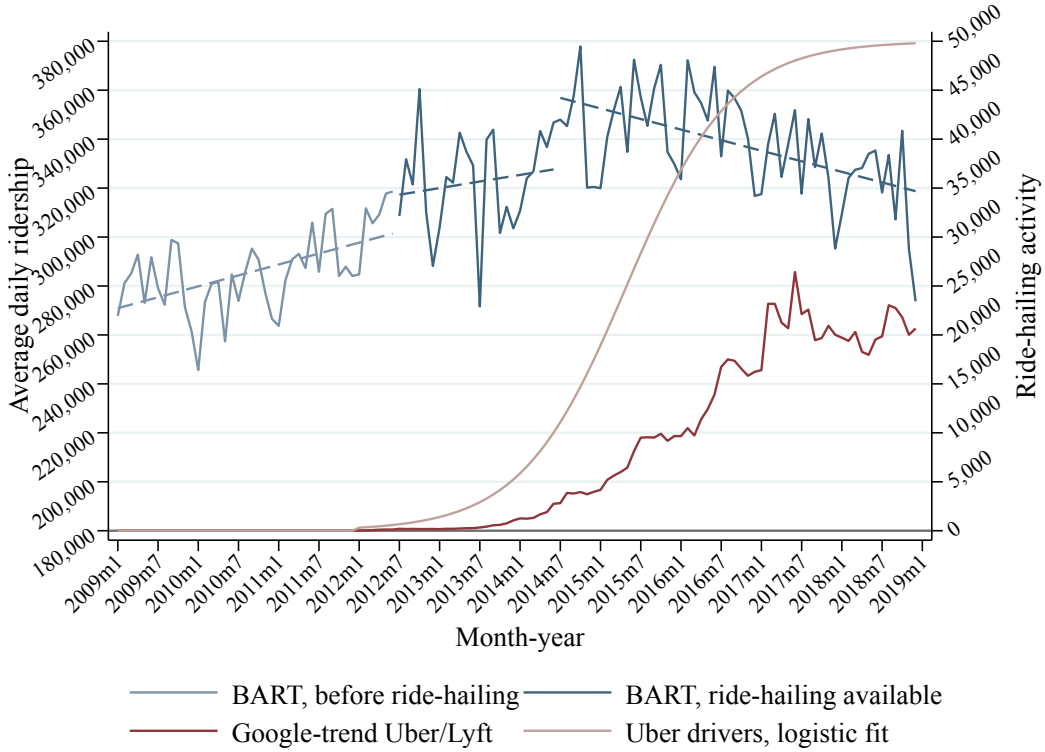
[2] See 'Ride-hailing is pulling people off public transit and clogging up roads' at www.technologyreview.com, accessed March 2020, and 'MTA Blames Uber for Decline in New York City Subway, Bus Ridership' at www.wsj.com, accessed April 2020.

market, ride-hailing is a substitute. They argue that the two rivals compete, which drives down the price of ride-hailing, making it more attractive form of transport. Alternatively, Coogan et al. (2018) measures cross-price elasticities between rail and ride-hailing for cities across the US, finding insignificant results, which suggests that ride-hailing and public transit are neither complements or substitutes. Similar to our study, Grahn et al. (2020) focus on one location, Pittsburgh, and a single mode of public transit, bus ridership. They correlate Uber surge-pricing to transit boardings, in ten minute increments across ten locations for six months. Their method does not identify causal mechanisms and lacks the ability to detect complementarity because the two modes must "split the pie" of total consumer base, which creates a structural substitution. However, their results vary by time of day and location, reinforcing the need to account for varying travel behavior. Finally, Erhardt et al. (2021) assess the impact of ride-hailing on San Francisco's Muni ridership. They use monthly data from mid-2009 to mid-2016 and compare ridership before and after ride-hailing is available. As in the previous paper, the method lacks identification and cannot find complementarity because the observations, for ride-hailing and public transit, aggregate monthly average weekday arrivals and departures together for each bus-stop.

Our work addresses gaps in the aforementioned studies. First, we assess detailed route-by-hour data over a longer time period, ten years — rather than monthly aggregate information over a few year, which allows analysis of the long-run trends and gives short-run variation of impacts in time and space. Second, we split the analysis into subsets of riders, such as commuters and airport transit, to provide insights beyond what the current literature yields. Therefore, we estimate who is affected, when and for how long. Most importantly, we determine why, by measuring three causal mechanisms to examine trade offs between public transit and ride-hailing. We contribute by directly addressing the question of how ride-hailing affects public transit.

Figure 1 demonstrates non-seasonal short-run fluctuations and provides a rationale for using an extended time period and a heuristic measure of the long-run trends. Before the arrival of *Uber*X and *Lyft* average daily BART ridership, as marked on the left axis, trends upwards by about 0.2 percent per month. The next time period is when ride-hailing takes off — this begins with the entry of both companies in July of 2012 and runs through mid-2014; we infer the length based on Google searches and the count of Uber drivers, as denoted by the right axis. In this period, BART ridership maintains a similar trend as

Figure 1. BART ridership through time versus ride-hailing growth, by month-year



Notes: Daily count of BART ridership on the left vertical-axis; truncated. Ride-hailing activity on the right vertical-axis, represented by (1) a Google searches, from `trends.Google.com`, and (2) a logistic-growth curve, fit to count of active Uber drivers. Trend lines: before ride-hailing, 0.2 percent increase in ridership per month; mid-2012 through mid-2014, no significant change in slope; and since July 2014, 0.2 percent monthly decline of ridership.

before ride-hailing; the growth is less steep, but not statistically distinct. Then, ride-hailing activity grows further and plateaus from 2017 to the present. During this mature phase of ride-hailing, BART ridership reverses trend and now declines, by 0.2 percent of ridership per month. Thus by the end of year, average ridership is down — by 60 to 85 thousand daily passenger-trips — from the trend before ride-hailing. These preliminary data suggest that ride-hailing has led to a decrease in public transit use.

In the next section, we describe a conceptual framework that allows either substitution or complementarity between public transit and ride-hailing. Each mode has many characteristics, which can vary by time of day and location. On one hand, public transit is affordable

and rail transit avoids traffic. However buses and trains are rigid in timing and location; the possibility of delays causes distress; and the riding conditions can irritate. In contrast, ride-hailing is point-to-point, on-demand and comfortable; yet it is more expensive than public transit and may be affected by congestion. Each consumer assesses the costs and benefits and makes the best choice. This simplified set up suggests several variables that may tip a consumer's decision: Cold temperatures and rain cause discomfort and traffic speeds alter time costs relative to public transit, thus weather and travel time are critical factors to test. Another dimension is that the correlation between morning and evening commuting should decrease when ride-hailing is available because using public transit both to and from work is less essential.

We estimate ride-hailing companies' impact on the San Francisco's Bay Area Rapid Transit (BART) system. Our first empirical strategy is a difference-in-differences approach to measure hourly effects by route. We use outdoor temperature and traffic speed as exogenous shocks for each route-hour and identify short-run effects. The temporal and cross-sectional variation allows us to measure how differences in weather and congestion affect public transit ridership when ride-hailing is available versus before ride-hailing exists. We also assess if ride-hailing affects the relationship between morning commuting and evening commuting — with Uber as an outside option, riders can decouple how they go to work from how and when they return home. Our second analysis compares daily ridership trends before and after ride-hailing is available, while controlling for numerous covariates. Additionally, we estimate heterogeneity by splitting the data into subsets by time of day, day of week, and location — as proxies for the purpose of travel.

We find that inclement weather and faster travel time each reduce BART usage more when ride-hailing is available than those variables do before ride-hailing. However we find a modest increase in the ratio of morning to evening commuters, indicating that 1-in-100 daily commuters ride transit into work but use ride-hailing after work. Comparing trends over the long-run, we find ride-hailing reduces BART ridership by 9.8 to 10.7 percent, year over year. Because use of ride-hailing grows through time, we break our data into phases to determine differential effects between when it is new to when it becomes the norm. Distinct from both Hall et al. (2018) and Babar and Burtch (2017), ride-hailing is a substitute for public transit in San Francisco during the first two years, the same period they test. For the commuter segment, ride-hailing availability decreases usage by a small amount,

presumably due to inelastic demand for and frequent use of public transit. Whereas, nighttime and airport transit have large decreases, year-over-year. Overall, *Uber*X and *Lyft* reduce ridership.

Each public transit authority must understand the effects of ride-hailing companies as it manages short-term changes in demand and, in the long-run, plans for operational and capital funding. To address the issue of complementarity or substitution, it is critical to take into account precise estimates about how hour and day has an impact on ride use for different types of riders. Different riderships in different locations can affect the relationship, thereby leading to different public policy conclusions. Furthermore, this is work is important because it has direct implications for social costs on communities and policy suggestions. Ride-hailing companies worsen road-surface quality, congestion, automobile collisions, and pollution levels; municipalities and other government bodies can use this information for regulations. Our method prioritizes ease of application, using commonly available public data sources. Transit authorities and municipalities worldwide can use our flexible and easy-to-implement methodology to evaluate the impacts of ride-hailing in their own region — on revenue and the costs of congestion, traffic collisions, and pollution.[3] Our findings and approach may assist them as they administer policies, coordinate with ride-hailing companies, and balance varying consumer needs.

2 A conceptual framework for transit demand

A rich literature in urban economics provides transit-demand models, which guide our hypotheses. Many studies rely on estimating discrete choices where a rider weighs the characteristics of their transit options and picks the best one. We use this previous literature to identify hourly and daily casual mechanisms, which we use in our panel-estimation methods, and for other variables available for municipalities. In fact, McFadden et al. (1977) forecast the demand for BART before it was constructed, using a discrete-choice framework. Here we review a simple descriptive framework and then describe the intuition for ride-hailing being a complement or substitute for a marginal public transit rider.

[3] We include complete, detailed instructions in Appendix A.3, providing the groundwork for varying data granularity and time frames.

A consumer trip from point A to B may use one or more modes, such as driving, ride-hailing, car-pooling, public transit, walking, biking, and parking. Each option has several dimensions contributing to consumer disutility. Disutility is a function of both direct and indirect costs: gas or fare; travel time; waiting time; discomfort due to weather, climate, and crowding; risk of delay and related stress; risk of harm via collision or assault; time costs for finding parking, and parking costs. By minimizing costs, a consumer makes a specific transit choice. We assess those consumers considering either public transit via rail or a ride-hailing as the two best options. As consistent with previous literature in transit, e.g. McFadden et al. (1977), we assume that a consumer's choice is independent from irrelevant alternatives. Thus, we rule out the other modes of transit.

Ride-hailing complements public transit when people can link the two modes. For example, public-transit users often struggle getting from their current location to a transit station or from the station to their final destination. This is called the "first/last mile" problem. Ride-hailing can bridge that distance, providing geographic flexibility to the fixed routes of public transit (Wang and Odoni, 2014). In other cases, a person may use public transit one way and ride-hailing the other, amplifying both modes of travel. Similarly, ride-hailing can respond quicker than public transit during emergencies, acting as insurance for those who typically choose public transit but may need immediate service once-in-awhile.

Substitution occurs when one transit option outweighs the other mode. Direct costs tip the scales toward public transit, which has lower average price than ride-hailing.[4] However, ride-hailing outperforms public transit in other dimensions. Ride-hailing innovations are increased convenience and information: rides are on-demand, hailed via a smartphone app, and deliver customers point-to-point, all while providing real-time information on arrival and transit time. Ride-hailing can lower the overall time spent in transit, relative to public transit, depending on traffic congestion. Additionally, ride-hailing offers more comfort than public transit, with better seating, privacy, and personalized climate control. Therefore, passengers substitute if they perceive that these amenities, relative to public transit, outweigh the higher price.

[4] Polzin (2016) estimates public transit costs at \$0.26/mile. Whereas ride-hailing is \$0.65 − \$2.00/mile, varying by location and time of day. Two examples: During 2017 on a weekday at 4pm, a trip from Embarcadero Station to the San Francisco Airport is \$8.95 via BART and around \$29.73 via *Uber*X. A trans-bay trip from Downtown Berkeley Station to the San Francisco Airport is \$9.55 via BART and around \$47.92 via *Uber*X; `www.sfoconnect.com/sites/default/files/document/TNCWhitePaper.pdf`, accessed January 2021.

If ride-hailing sufficiently changes consumer disutility, relative to public transit, then we will observe a change in ridership.[5] We hypothesize that effects differ temporally, by month of the year, by day of week, by time of day. In addition, the effects should vary with the origin and destination, which proxy for a rider's purpose.

3 Empirical context and data descriptions

Our empirical setting is the San Francisco Bay Area.[6] We gather a decade of data, from 2009 to 2018; source descriptions in Table A-1. The outcome is ridership of Bay Area Rapid Transit (BART) as hourly counts by route: total passengers from each origin station to any destination station. The treatments are the establishment and prevalence of ride-hailing. We also assemble covariates that affect BART ridership and demand for ride-hailing.

BART is an electric railway system with services throughout San Francisco (SF) and the greater East Bay; Figure 2. The system has 48 stations, connecting eight endpoints. Each pair of stations, an origin and a destination, is a route. We limit our analysis to the 44 stations in operation by 2014, thus our data have 1,892 distinct routes. BART collects data on ridership, performance, safety, and several other aspects, and then publishes them to `data.bart.gov`. Our primary data consist of 137.4 million hourly observations, Table 1. We use these data for most analyses, but for some empirical models, we aggregate to daily count of trips-by-route, which has over 6.6 million observations.

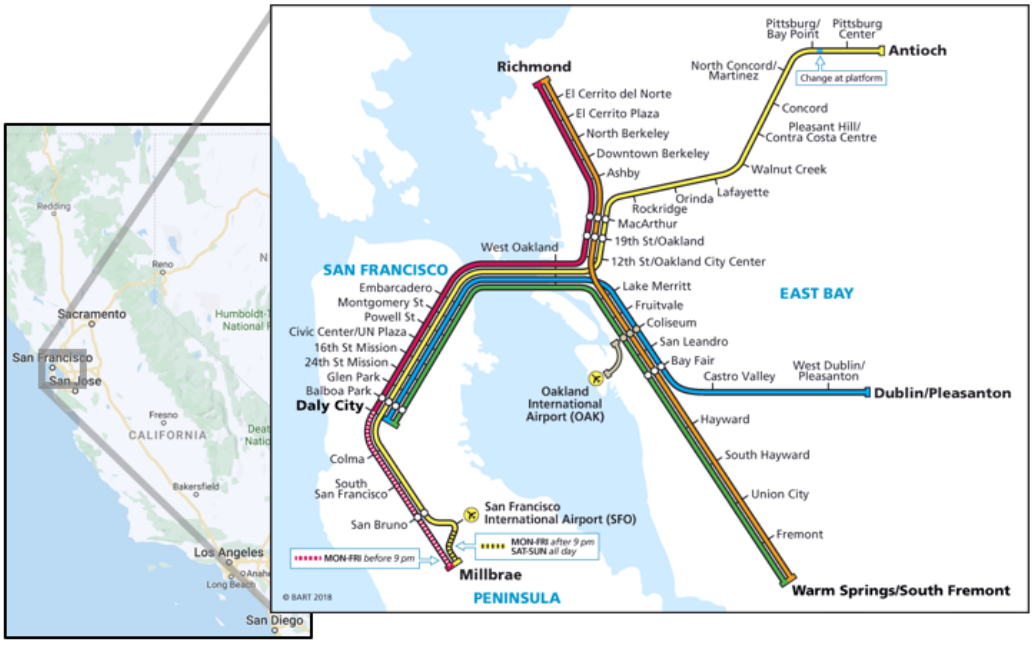
BART has nearly 310,000 passenger-trips per day, on average. Looking again at Figure 1, ridership grew from 2009 through 2013, peaking at around 380,000 passenger-trips per day in early 2014, then declined in the recent years. BART ridership fluctuates by month: November, December, and January have fewer passenger-trips per day, whereas ridership is higher during June and August through October. The daily numbers of passenger-trips per route varies widely too, from none to over 6000, averaging 170 per route-day.

The hourly ridership average, pooled over all data, is 8 passengers per route. However,

[5] Some consumers are infra-marginal; i.e., always choosing public transit. For these riders, ride-hailing and public transit neither compete against nor complement. This dampen our estimates, as we measure average treatment effects.

[6] We discuss external validity in the Conclusions section. In the Appendix, we provide a template for other municipalities to estimate the effects for their regions.

Figure 2. BART route map, effective September 2018



this varies widely, from none to 1,826 on a single route. We split ridership into groups using hourly patterns in our data and consumer surveys. We establish the following seven groups: 1) airport transit to SFO, 2) airport transit from SFO, 3) morning commuters, 4) evening commuters, 5) daytime recreation, 6) nighttime recreation, and 7) all other route-hours; details provided in the appendix, with summaries in Table A-2 and Figure A-2.[7] *SFO Airport* and *Recreational* route-hours and *All other* ridership each have 5 to 7 passengers per route-hour; Table 1. *Commuter* route-hours have 12 to 19 times higher BART ridership, with 88 and 85 passengers per route-hour, AM and PM respectively; observations are the three-hour windows, morning and evening, and 314 routes heading into or out of the downtown core.

Several indicator variables account for BART schedules and rider demand, given as proportions in Table 1. *Workdays* indicate Monday through Friday, which have more ridership than *Weekends*. Three types of holidays, *BART holiday*, *Federal*, and *Recreational*, allow

[7]BART opened a station at Oakland Airport after ride-hailing entered the market, data which we include in 'all other route-hours' and which contributes to estimation of rider trends.

Table 1. Summary statistics

Continuous variables	Obs.	Mean	S.D.	Min.	Max.
BART ridership					
Daily total count	3,638	308,205	109,730	2,670	548,731
Route-by-day count	6,622,374	169.31	305.69	0	6,374
Route-by-hour count	137,418,912	8.16	25.91	0	1,826
Route-by-hour count, by group:					
SFO airport, to	3,231,169	6.13	12.20	0	429
SFO airport, from	3,195,787	6.86	14.72	0	530
Commuters, AM	2,358,119	87.66	98.69	0	1,317
Commuters, PM	2,360,327	84.54	81.26	0	1,463
Recreational, day	49,165,317	6.70	14.19	0	1,826
Recreational, night	18,548,655	4.81	13.53	0	1,366
All other route-hours	62,029,327	4.55	12.88	0	1,539
Avg temperature F°, route-hour	137,418,912	59.209	8.958	25	109.9
Rain ″, hour	87,648	0.002	0.012	0	0.380
Highway speed, mph, route-hour	136,004,391	62.0	6.4	12.9	78.3
Population, 1000s, month	120	4,417.1	154.5	4,188.1	4,673.2
Employment, 1000s, month	120	979.8	101.9	845.0	1,156.6
VMT, 1000s, day	6,622,374	59,125	5,663	32,620	71,088
Gas price, real $, week	520	3.738	0.587	2.34	5.155

Indicator variables, as proportions

BART characteristics		Other characteristics	
Workday	0.743	Ride-hailing in SF	0.663
Weekend	0.257	Ride-hailing widely available	0.466
BART holiday	0.019	Federal holiday	0.027
Busy SFO travel date	0.069	Recreational holiday	0.011
		Rainy hour	0.067

Note: Data from January 1, 2009 to December 31, 2018. The time-unit of observation for each continuous variable is listed after the variable name. VMT is vehicle miles traveled, as measured on surface streets in the SF-OAK metro areas. Proportions calculated from hourly data.

differential responses to each. BART observes eight holidays, implementing a Saturday- or Sunday-schedule. *Federal holidays* are *BART holidays* plus Easter, Native American's Day, and Veteran's Day. *Recreational holidays* are Valentine's Day, St. Patrick's Day, Cinco de Mayo, and Halloween. In addition, we create an indicator for *Busy SFO travel dates*, based on transit to/from the airport, which are days around holidays.

Uber Technologies Inc formed in 2009 and began operating in San Francisco in 2011, offering luxury, black-car services. Uber's popularity rose in mid-2012 with the introduction of *Uber*X, a cheaper service; *Lyft* entered simultaneously in San Francisco. Sixty-six percent

of our observations occur after the two services launched in San Francisco on July 1, 2012 and are indicated by *Ride-hailing in SF*. Yet, adoption of ride-hailing technology by drivers and consumers is gradual. Thus, we divide our decade of data into three phases: before ride-hailing, adoption of ride-hailing, and mature. The before ride-hailing phase occurs before *UberX* and Lyft launch in SF. The ride-hailing adoption phase is when the number of drivers begin to take off and consumers start using the service more regularly. The data on ride-hailing activity indicate that two years pass before Uber and Lyft are prominent and rooted in SF. Therefore, the period after July 1, 2014 is the mature phase, when ride-hailing has a large supply and demand.

We use two exogenous variables — weather and highway traffic speeds — to identify mechanisms by which ride-hailing changes transit ridership. We collect these data by hour and at numerous locations, to create cross sectional variation. These aspects directly affect transit and interact with the choice to use ride-hailing, once the services become available. Our route-by-hour weather measurement is the temperature at weather station nearest the BART entry, lagged by one hour, averaged with the temperature nearest the BART exit. Average temperatures hover near 60° Fahrenheit, with a standard deviation of 9°. Around seven percent of all date-hours have rainfall. Finally, we create a proxy for driving speed, for each date-hour by route, in miles per hour (mph). Driving speed is inversely related to travel time which affects choice of transit. We collect traffic speed data measured by highway sensors near a route's origin and destination, then average the speeds that match direction of travel for the route. Additional details on these variables are in A.1.

Additional covariates capture important trends that affect transit, including monthly data on population, employment, and vehicle miles traveled, and local gas price by week, converted to 2018$; see Summary Statistics, Table 1. These are necessary for our long-run analysis, which compares time trends before and after ride-hailing. For robustness, we also test numerous other variables, which we find do not impact our estimated impacts on ridership; these include train on-time performance metrics, BART fares, BART fatalities, crime, air traffic, the #deleteUber twitter movement, and amount of daylight. For our short-run analysis, we drop the monthly time-series variables and exploit several forms of time fixed effects, which capture constants-by-time, including unobserved trends.

4 Empirical analysis

In this section, we analyze the short-run impacts of ride-hailing on BART ridership and then assess long-run trends. For each, we lay out our specification and determine the effects for the full sample of data. We follow with results by ridership group — commuters, recreational, and airport transit — to assess heterogeneous effects on trips by time of day, purpose, and location.

4.1 Short-run: difference-in-differences by cause

We determine how ride-hailing affects BART ridership, as identified by variation in two exogenous mechanisms — weather and traffic speeds. Both weather and traffic speed have panel-level variation by route-hour. We implement difference-in-differences to test for the effects on public transit ridership, before and with the availability of ride-hailing. Variations in these factors each cause fluctuations in ridership by changing the trade-offs between modes of transit. We estimate how a factor affects transit before ride-hailing.

We use a panel regression model:

$$\text{bart}_{ih} = [\text{F}_{ih}]' * \boldsymbol{\alpha} + [\text{F}_{ih}]' * \text{RH}_h * \boldsymbol{\Gamma} + X'_h * \boldsymbol{\zeta} + \boldsymbol{\gamma_i} + \boldsymbol{T}_h + \epsilon_{ih}.$$

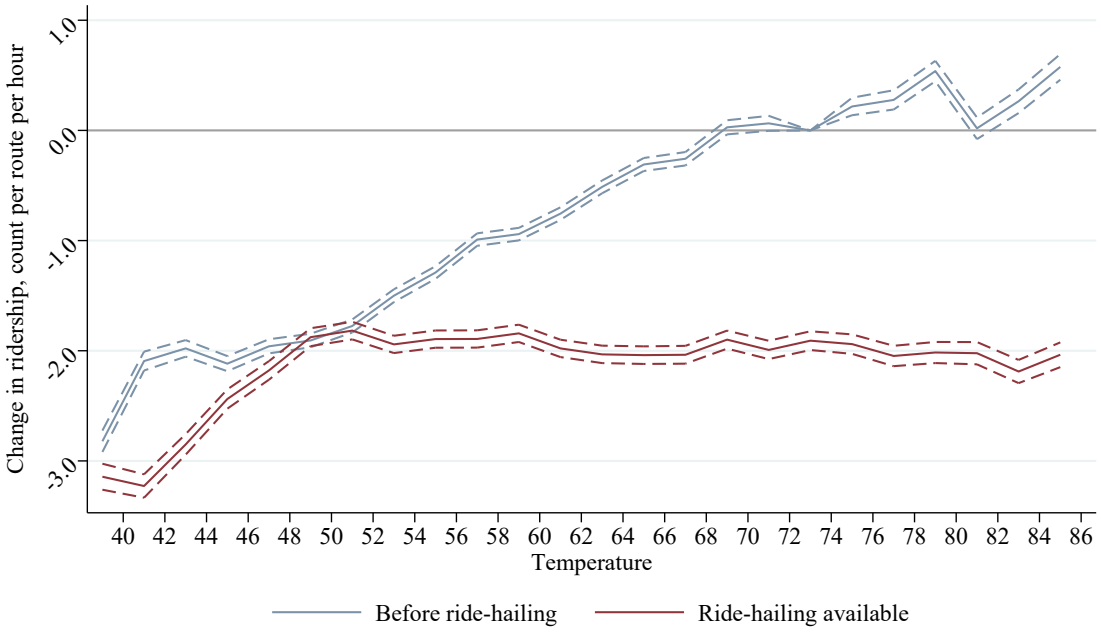
The outcome variable, *bart*, is hourly BART ridership, indexed by route i and hour of date h. The specification is difference-in-differences, before versus during ride-hailing availability. The $[F]$ is a placeholder for each factor; these variables are continuous so create bins. We estimate a separate specification for each causal mechanism. The dummy variable RH indicates ride-hailing is available, thus RH takes the value 1 if the observation occurs July 1, 2012 or later. $\boldsymbol{X'_h}$ is a collection of covariates. The $\boldsymbol{\gamma_i}$ is a vector of route fixed effects. Time fixed effects, $\boldsymbol{T}_t$, account for month-year, day of week, and hour of day. The coefficients in vector $\boldsymbol{\alpha}$ are the effects of the $[F]$-bins on *bart* ridership before ride-hailing entered the transit market. Our primary estimates are the $\boldsymbol{\Gamma}$ coefficients on the RH-$[F]$-bin interaction terms, as they measure how BART ridership changes when ride-hailing is available. Positive value implies that ride-hailing complements public transit, whereas, a negative value signals substitution. We use ordinary least squares estimation and cluster

the standard errors by route to account for potential serial correlation.

Our first factor is weather. People using public transit are more exposed to the weather than if driving or riding in a car — facing bigger repercussions from precipitation and variation in temperature, in particular, when getting to and from transit stations. We expect that extreme temperatures or rain reduce BART-ridership demand. Ride-hailing offers shelter from the storms and temperature swings, thus we hypothesize that when these undesirable weather factors are present, ride-hailing is a substitute for public transit. Furthermore, weather is exogenous, providing a plausible causal mechanism of how ride-hailing and public transit interact. We use interactions of weather variables with ride-hailing availability to identify this mechanism. Specifically, we create indicator bins for every two-degrees, by each hour: $\sum_{d=38}^{78} \text{bin}_{d,ih}$. We exclude the bin centered on 73°F for before ride-hailing. We include an indicator variable for a rainy hour, in the $[F]$ matrix; therefore we measure the interaction of rain with ride-hailing availability as well. Covariates include the proportion of hour day-lit, hourly route-specific travel speed, and indicators for holidays and busy travel days. Time fixed effects for each month-year, day of week, and hour of day control for underlying trends, seasonal and weekday transit patterns, and intra-day demand that are common across all routes.

We estimate results using three time windows: (1) omitting the first two years of ride-hailing, (2) for the entire decade, and (3) breaking the period of ride-hailing into phases, setting two years for adoption. We provide the results from (1) because they are the most conservative; others available on request. We summarize the findings with figures, one for the full data set and three additional for our groups, *Commuter*, *Recreational*, and *Airport* transit. The overall pattern is clear: before ride-hailing is established extreme temperatures and rain reduce demand. When ride-hailing is available, demand is further reduced for most temperatures and for rainy hours, compared to before the availability of ride-hailing. Figure 3 provides the temperature results for all ridership. For the period before ride-hailing, ridership is highest in the range of 68 to 76 F°, which coincides with comfortable ambient temperatures. Whereas, passengers per hour decrease linearly as temperatures drop. The line for "Ride-hailing available" represents the impact. When ride-hailing is present as an alternative mode to BART, ridership falls for all temperatures except for bins 48 to 52 F°. The Uber-effect is around one passenger per route-hour in the ranges of 40 to 46 F° and 52 to 56 F°. Above 56 F° the impact increases to two

Figure 3. BART ridership responses to temperature,
before and with ride-hailing availability

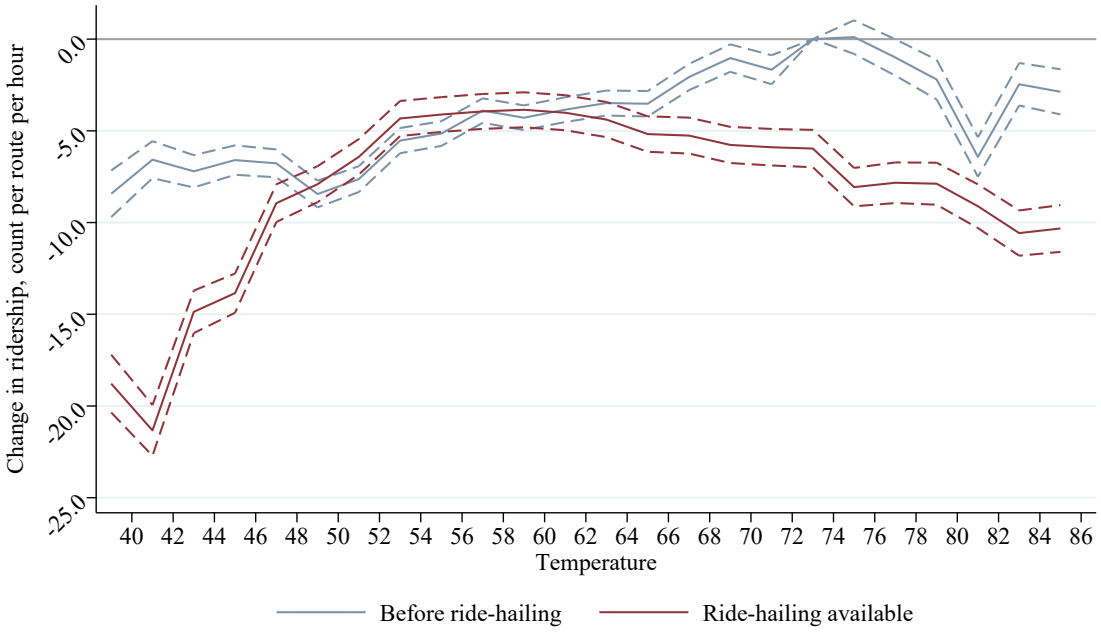


Notes: Two-degree temperature bins, centered on odd values. Adoption period July 2012 to June 2014 omitted. Dashed lines represent 95% confidence intervals.

passengers lost per route-hour. These translate to ride-hailing inducing losses of 0 to 25 percent, depending on the temperature. A rainy hour decreases ridership by 1.6 passengers per route-hour, or 19.7 percent. Once ride-hailing is available, rain does not significantly change the magnitude of lost ridership.

The results by public-transit ridership group demonstrate heterogeneity and confirm our intuition and hypotheses. Even with availability of ride-hailing, commuters are fairly insensitive to changes for moderate ambient temperatures, between 48 and 64 F°; Figure 4. However for cooler temperatures, the commuter ridership before ride-hailing drops an additional rider per route-hour for every two-degree bin, with 15 fewer passengers per route-hour in the 40-42 F° bin. In percent terms, these changes values are smaller than the overall effect above because commuter route-hours have 10 times more passengers than the pooled average. The impact once ride-hailing is available during extreme temperatures is a loss of about 8.2 people in the coolest weather and about 4.7 passengers during warmer weather.

Figure 4. BART Commuters' responses to temperature,
before and with ride-hailing availability

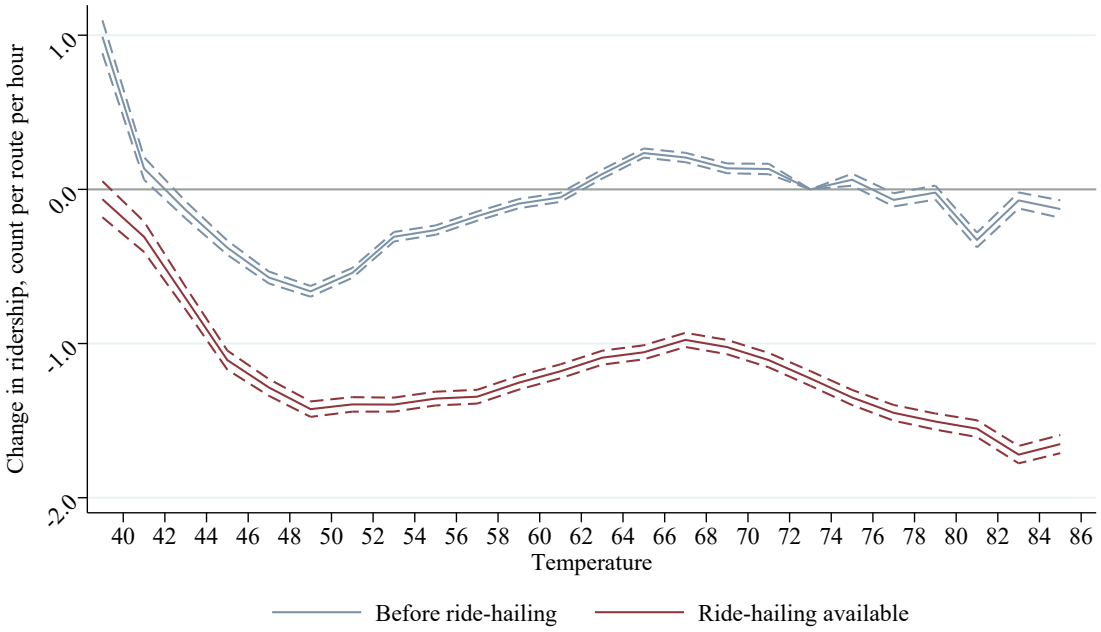


Notes: Two-degree temperature bins, centered on odd values. Adoption period July 2012 to June 2014 omitted. Dashed lines represent 95% confidence intervals.

In addition, a rainy hour causes 5 fewer commuters per route-hour, before ride-hailing, and 0.2 fewer commuters when ride-hailing is an available substitute, which is a 0.023 percent loss; however, the result is not statistically significant. Figure 5 provides results for recreational trips: the substitution effect when ride-hailing is present for the temperature is about 1 to 1.5 passengers per route-hour, or 16.4 to 24.6 percent. With ride-hailing availability, rain reduces hourly recreational passengers by 2.1 percent. Figure 6 provides results for transit to and from the San Francisco International Airport; again, ride-hailing causes losses to ridership. The gap ranges from 1 to 2 passengers per route-hour, or 20.8 to 41.6 percent. During a rainy hour that has ride-hailing availability, airport transit is 2.9 percent lower. According to the weather results, ride-hailing crowds out public transit.

Our second causal factor is highway traffic speeds. Time saving is one of the main reasons for choosing to take ride-hailing over public transit (Feigon and Murphy, 2018; Rayle et al., 2016). In the Bay Area, driving is usually faster than public transit. Before the availability

Figure 5. Recreational responses to temperature,
before and with ride-hailing availability



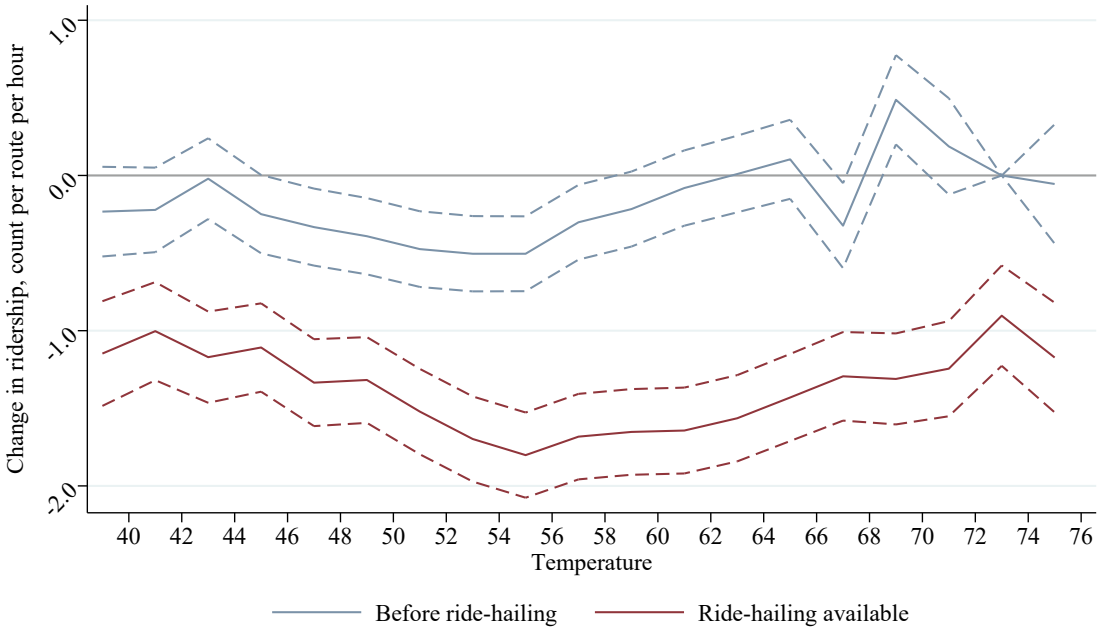
Notes: Two-degree temperature bins, centered on odd values. Adoption period July 2012 to June 2014 omitted. Dashed lines represent 95% confidence intervals.

of ride-hailing, we posit that during hours with slower-than-normal vehicles speeds, those who drive may shift to BART, causing BART ridership to increase. Now that ride-hailing is available, we hypothesize that ride-hailing will reduce BART ridership for speeds in the range of free-flowing traffic. However, there are slow speeds at which point ride-hailing no longer prevails in the dimension of travel-time cost. We call this speed the "cross-over" point and expect that at speeds lower than this, the availability of ride-hailing increases public transit as more people opt to avoid traffic congestion.

We approximate speed, in mph, for every hour of each BART route by averaging origin and destination speed-by-direction of travel.[8] We create indicator bins, defined by 5-mph speeds for each route-hour, ih: $\sum_{d=40}^{75} \text{bin}_{d,ih}$. We exclude a before-ride-hailing bin, from 65 up to 70 mph, centered on 67.5 mph. Covariates include hourly weather variables, the

[8]For robustness, we also test two other time measures: an approximation of travel time and occurrence of bottlenecks, which are unexpected traffic jams. These data are poorer in quality and require more assumptions than our speed measures, but the results are similar.

Figure 6. SFO responses to temperature,
before and with ride-hailing availability

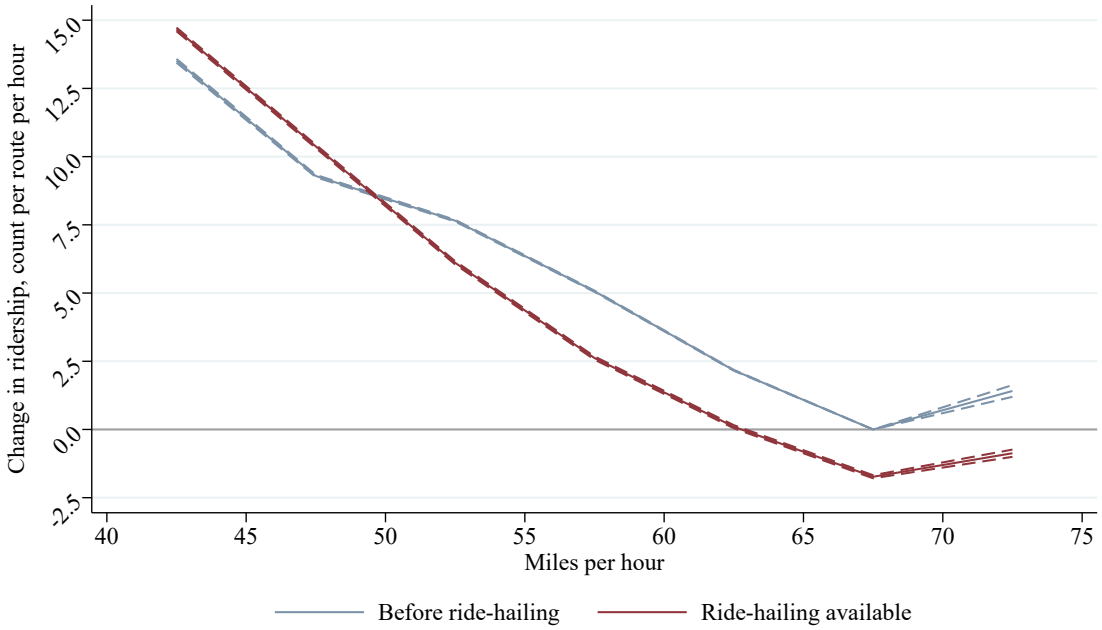


Notes: Two-degree temperature bins, centered on odd values. Adoption period July 2012 to June 2014 omitted. Dashed lines represent 95% confidence intervals.

proportion of hour day-lit, and indicators for holidays and busy travel days. Time fixed effects for each month-year, day of week, and hour of day control respectively for underlying long run trends, seasonal and weekday transit patterns, and intra-day demand outcomes that are common across all routes.

As shown in Figure 7, before ride-hailing exists, more consumers choose BART as speeds decrease away from free-flowing traffic of 65 to 70 mph. As highway speeds slow to around 40 mph, about 13 more people choose public transit per route, per hour. With ride-hailing available, fewer passengers choose BART at high speeds because of reduced time costs, but this wedge narrows as traffic speeds decrease and at speeds below 50 mph, more passengers choose BART. This cross-over point may indicate consumers' change in willingness to pay for time savings — a relatively high speed may indicate that consumers are more elastic to travel-time costs and vice-versa. Or the point might reflect the availability of outside options for distinct travel segments. Cross-over at a lower speed implies less elastic demand

Figure 7. BART ridership responses to highway speeds



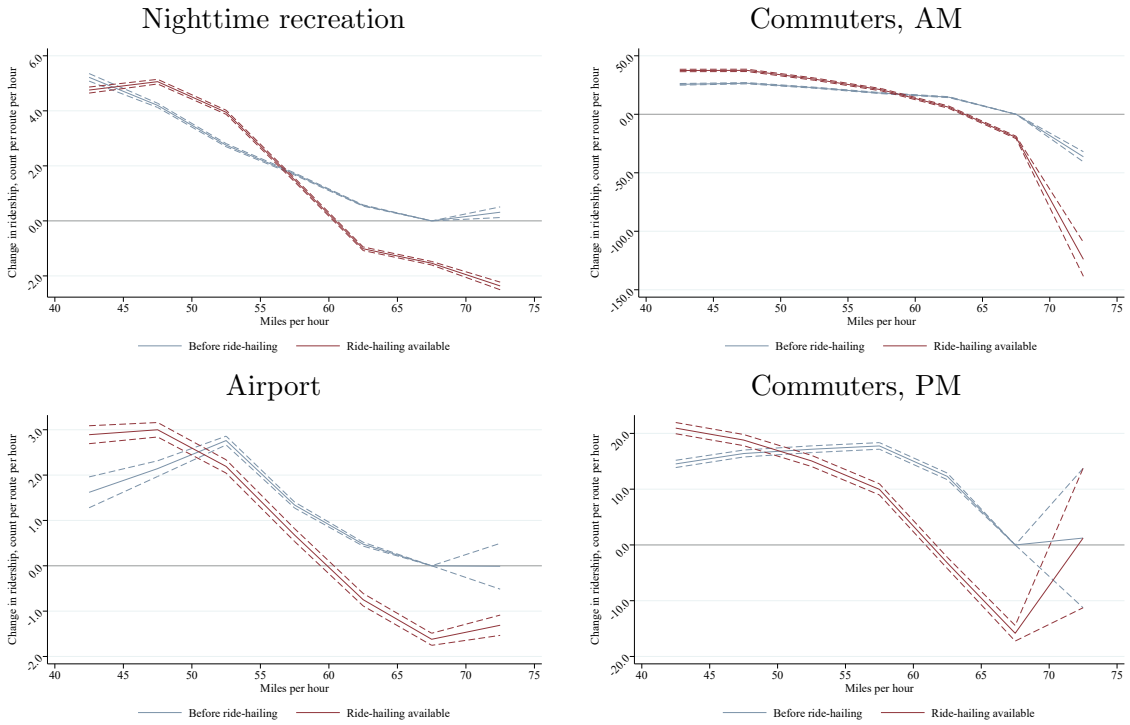
Notes: Each bin is 5 mph: 40-45 mph, 45-50 mph, ..., and so on. We exclude the before-ride-hailing bin 65-70 mph, centered on 67.5 mph.

with respect to time.

Decomposing these results by group provides additional features of relationship between highway speed, public transit and ride-hailing; Figure 8. There is large variation in magnitudes between and within groups: Very little change of ridership occurs for airport transit; the spread over speeds is less than twenty percent of the standard deviation. Whereas there are enormous changes for commuters, particularly in the morning, which ranges from 25 more riders at slow driving speeds to almost 50 fewer at fast speeds — representing 75 percent of the standard deviation. Furthermore, if the cross-over point occurs at a lower speed, the group seems more inelastic to changes in travel time. In other words, airport and evening commuters appear more tolerant of longer travel times, whereas morning commuters and nighttime recreation passengers are more responsive and shift to transit at lower road speeds.

We also analyze the impacts on commuter round-trips, i.e., how ride-hailing affects public

Figure 8. BART ridership responses to highway speeds, by group



Notes: Available in the appendix, results for daytime recreational, to/from SFO separately, and other.

transit to work versus home, using difference-in-differences analysis. Once ride-hailing is available, transit riders have a new outside option for either direction of a round trip: they can split the two directions into different modes of travel. Commuters can more easily decouple how they get to work from how they return home. Thus, we hypothesize that public transit in the morning complements evening ride-hailing and vice-versa. We test for this relationship using commuter route-hour subset of data. We collapse these data to average ridership per route for all hours of morning commuting and merge those to the same day's evening commutes. We regress morning ridership and its interaction with the availability of ride-hailing on evening ridership by date and route, per the specification at the beginning of this section, 4.1. We find that once commuters can 'take an Uber' in the evening, about 1 in 100 do so each day. This result is robust to several variations of covariates, including using non-rush-hour ridership to control for a secular trend in ridership. An alternative explanation is that more people use ride-hailing in the morning,

with the expectation of using public transit home. However our former interpretation is more consistent with greater inelasticity of morning commuters and anecdotes about having and desiring more flexibility in the evening.

4.2 Long run: comparing trends before ride-hailing and during its availability

In our long-run estimate, we compare daily trends in BART ridership, before ride-hailing companies and then with ride-hailing availability. We estimate the change in daily ridership by route, for each additional day that ride-hailing is available. The long-run results are an average over all years, and the findings provide the cumulative effects of ride-hailing, year over year. Our regressions are fixed-effects panel specifications:

$$\text{bart}_{it} = \begin{cases} \beta_0 d_t + \beta_1 \text{RH}_t + \beta_2 d_t * \text{RH}_t + X'_t * \boldsymbol{\Gamma} + \boldsymbol{\gamma_i} + \boldsymbol{T}_t + \epsilon_{it} \\ \beta_0 d_t + \beta_1 \text{RH}_t + \beta_2 d_t * \text{RH}_t + \beta_3 \text{RH_m}_t + \beta_4 d_t * \text{RH_m}_t + X'_t * \boldsymbol{\Gamma} + \boldsymbol{\gamma_i} + \boldsymbol{T}_t + \epsilon_{it} \end{cases}$$

As above, the outcome variable, *bart*, the count of BART passenger-trips for route i , but now aggregated to date t. The top equation represents a simple comparison of before ride-hailing and when ride-hailing is available. d_t is the sequential date, providing the time trend for before ride-hailing is available. The dummy variable RH is defined as before. $\boldsymbol{X'_t}$ is the collection of covariates: daily temperature low and high, a rainy day indicator; holiday indicators for BART scheduling, Federal, and recreational days; and the 25 busiest travel days by year to/from SFO. $\boldsymbol{X'_t}$ also includes monthly time-series for SF-area population, employment, and traffic congestion, and weekly gas prices. The $\boldsymbol{\gamma_i}$ is a vector of route fixed effects. We account for the month-of-year and day-of-week with time fixed effects, $\boldsymbol{T}_t$. β_0 is the linear time trend in *bart* ridership, conditional on other controls, before ride-hailing companies entered the transportation market. The β_1 estimate is a constant intercept without meaningful interpretation. The coefficient, β_2, on the interaction, $d_t * RH_{it}$, is our fundamental estimate as it measures how the ridership changes for each additional day of ride-hailing availability. Again, a positive value implies that ride-hailing complements public transit, whereas, a negative value signals substitution.

The bottom equation splits the availability of ride-hailing into two periods, modeling the trend-lines in Figure 1. The dummy variable, *RH-m* indicates that ride-hailing is widely available and in use in the SF area, i.e., "mature." We use a period of two years for these

main results and test robustness of results to varying lengths, in the appendix. Thus, the other result of primary interest is β_4, which provides the change in trend, for each additional day, after ride-hailing reaches maturity compared with the early phase of ride-hailing. The interpretation of the β_4 estimate depends on the sign of β_2. Thus, we perform a linear t-test of $\beta_2 + \beta_4$ to determine the joint effect of ride-hailing availability: If the joint result is greater than 0, the net effect of ride-hailing, in the long run, is complementary to public transit, less than 0 implies that the two modes are substitutes.

Again, we find the entrance of ride-hailing companies reduces ridership. We use ordinary least squares estimation, and we follow the now-standard protocol of clustering standard errors by route to account for potential serial correlation. Table 2 reports the results. Column (1) omits the first two "adoption years" of ride-hailing availability. The effect of ride-hailing is 5.5 million trips lost system-wide annually or 5.4 percent of average annual ridership. We use this value for our calculations of long-run social costs in the next section. Column (2) estimates the simple before/after-trend model and does not distinguish between the adoption and mature period. The overall effect of ride-hailing availability is similar. The *Date* trend in ridership, prior to ride-hailing availability, is negative and significant, -0.02 trips lost per route-day — a decrease of 43 BART trips per additional day over all routes. Our results concur with Manville et al. (2018a), which shows that population growth in Southern California outpaces the proportion who use transit. In column (3), we estimate the impact of ride-hailing during the first two-years versus the mature period. The impact of ride-hailing is 30 fewer trips per additional day. Once ride-hailing is widely available, the loss of BART ridership further decreases by 51 trips per additional day. We use a t-test to determine the *Overall effect of ride-hailing availability*, -0.0427 trips per route per additional day. The results for the substitution effect are similar across all specifications: overall, ride-hailing is associated with a *year-over-year loss* of 9.8 to 10.7 percent.[9]

Table 2 also reports the estimates for the covariates; the signs conform to our hypothesized effects. Ridership is correlated with population increase, except for the in (3) where

[9]To determine percent change, the numerator is the estimated marginal effect per additional day on a route's ridership times 365 days in a year. The denominator is the average ridership per route, before ride-hailing, multiplied by the number of routes. Dividing these gives the average annual percent change. We test for sensitivity by making several modifications to the specification: we include lag and lead variables (Table A-4), vary the length of the adoption period (Table A-3, and add several other month-varying independent variables).

Table 2. Long run: Comparison of daily ridership trends, pre- and during ride-hailing availability

Variables	(1)	(2)	(3)
Date	-0.0011	-0.0228**	0.0053**
	(0.00204)	(0.00181)	(0.00160)
Date*Ride-hailing		-0.0466**	-0.0156**
		(0.00205)	(0.00125)
Date*Ride-hailing*Mature	-0.0447**		-0.0271**
	(0.00195)		(0.00148)
Overall effect of ride-hailing availability, (*t-test*)	-0.0447	-0.0466	-0.0427
	(0.00195)	(0.00205)	(0.00189)
Post-estimation calculations			
Daily Δ in trips, at year's end	-30,849	-32,193	-29,509
%-Δ in trips, at year's end	-10.25	-10.69	-9.803
Annual Δ in passenger-trips	-5,529,943	-5,875,223	-5,385,393
Population	-0.1793**	0.2908**	-0.2988**
	(0.03948)	(0.02383)	(0.02957)
Employment	0.4117**	0.4386**	0.4009**
	(0.01997)	(0.02053)	(0.01930)
ln(Gas price, real $)	12.4344**	6.2072**	12.6172**
	(1.26143)	(1.32123)	(1.22979)
Daily VMT (1000s), 3-day moving avg	0.0023**	0.0020**	0.0020**
	(0.00010)	(0.00009)	(0.00009)
Temperature F°, low	0.4643**	0.6941**	0.5477**
	(0.03673)	(0.04145)	(0.03850)
Temperature F°, high	0.0872**	0.1338**	0.1173**
	(0.01743)	(0.01666)	(0.01674)
Rainy day	-3.1426**	-3.3602**	-3.0873**
	(0.18208)	(0.18751)	(0.17982)
Observations	5,317,808	6,622,374	6,622,374
R-squared	0.161	0.161	0.161
Route FEs	1,892	1,892	1,892

Note: Outcome is daily BART ridership per route; the treatment is an additional day of ride-hailing availability. Column (1) omits the first two years of ride-hailing availability, whereas column (2) keeps this period. Our social cost estimates are based off of column (1). Column (3) estimates the impact of ride-hailing availability separately for the first two years relative to when ride-hailing is widely available. Robust standard errors clustered by route; ** p<0.01, * p<0.05.

the *Date*-trend switches sign too. As employment rises in the region, transit demand increases. When gas price rises, the cost of driving increases and consumers substitute away from automobiles, increasing BART ridership. BART ridership and vehicle miles traveled (VMT), which is a measure of automobile activity, increase together in response to regional demand. We find more BART trips in warmer weather and fewer on rainy days.

In Table 3, we decompose the results of column (3), by ridership group, to obtain the respective effects for airport travel, commuters, and recreational transit. The results for before and during ride-hailing availability follow the pattern from the complete data set. However, the magnitudes vary by group, and mostly follow our hypotheses. We first assess routes to and from SFO Airport, with public transit to and from SFO falling by 10.5 percent, year-over-year, about the same as the overall average. Next, we estimate effect on commuters. We hypothesize that ride-hailing has less influence on commuters because demand is inelastic with respect to getting to work each day. Indeed, both morning and evening rush-hour routes have smaller losses than average, 9.4 percent and 6.7 percent annually. We expect recreational transit to have the most flexibility and exhibit larger effects. However, the daytime reduction is 8.7 percent, indicating this group may include a less-elastic segment of passengers. The nightlife results bear out our intuition — ridership has been dropping precipitously, by an average of 17.4 percent per additional year. The 'Other' category is too broad for a practical explanation. Adding up all groups' annual change in trips gives a total loss of 6,410,530 trips, which squares with the overall estimates above.

A concern with these long-run results is the main issue with any before-after comparison: we worry that an unobservable or unaccounted trend is affecting the outcome at the same time as the treatment of interest. Suppose an omitted factor is driving down BART ridership during the same period of growth in ride-hailing availability. Then we have wrongly attributed ride-hailing as the cause.

Fortunately, several aspects alleviate this concern. First, we look at demographic trends. Over our period of study, population and employment opportunities have risen in the Bay Area. Air traffic to/from SFO and OAK has trended up for the entire decade (`data.sfgov.org`). Bay-area residents own fewer cars over the the latter half of this decade, which should increase the demand for both public transit and ride-hailing. These prevailing forces are likely to increase demand for BART, and thus, we may be underestimating the long-run

Table 3. Long run: Comparison of daily ridership trends, pre- and during ride-hailing availability, by group

Variables	SFO	Comm, AM	Comm, PM	Rec, day	Rec, night	Other
Date	0.0071**	-0.0564**	-0.0391**	0.0010	0.0004	0.0012
	(0.00246)	(0.00514)	(0.00378)	(0.00066)	(0.00041)	(0.00065)
Date*Ride-hailing	-0.0011	-0.0690**	-0.0405**	-0.0025**	-0.0054**	-0.0083**
	(0.00219)	(0.00592)	(0.00465)	(0.00071)	(0.00042)	(0.00050)
Date*Ride-hailing*Mature	-0.0113**	0.0110**	-0.0003	-0.0092**	-0.0051**	-0.0050**
	(0.00230)	(0.00384)	(0.00331)	(0.00063)	(0.00032)	(0.00044)
Overall effect of ride-hailing availability, (*t-test*)	-0.0125**	-0.0580**	-0.0408**	-0.0117**	-0.0106**	-0.0133**
	(0.00241)	(0.00574)	(0.00445)	(0.000537)	(0.000545)	(0.000520)
Post-estimation calculations						
Daily Δ in trips, at year's end	-382.7	-6,653	-4,679	-7,683	-6,961	-8,768
%-Δ in trips, at year's end	-10.53	-9.405	-6.710	-8.666	-17.35	-11.72
Annual Δ in passenger-trips	-69,834	1,214,173	-853,918	1,402,148	1,270,383	1,600,160
Population	-0.1376**	1.1248**	0.7837**	-0.0253	0.0210*	0.0036
	(0.04396)	(0.12345)	(0.09372)	(0.01552)	(0.00828)	(0.01265)
Employment	0.0912**	0.4534**	0.2927**	0.0488**	0.0456**	0.0730**
	(0.01674)	(0.03522)	(0.02745)	(0.00424)	(0.00326)	(0.00354)
ln(Gas price, real $)	1.2294	8.1642**	3.1359	1.0198**	-0.7283**	-0.4522
	(0.78856)	(2.25736)	(2.19619)	(0.33963)	(0.23874)	(0.31438)
Daily VMT in 1000s	0.0011	-0.0190**	-0.0129**	-0.0003*	-0.0006**	-0.0009**
	(0.00059)	(0.00175)	(0.00133)	(0.00015)	(0.00010)	(0.00014)
Temperature F°, low	-0.0631	-3.5352**	-2.1822**	-1.3763**	0.1536**	-0.2130**
	(0.03175)	(0.19510)	(0.10527)	(0.11405)	(0.02415)	(0.02012)
Temperature F°, high	0.0934**	4.5130**	2.3685**	1.0460**	-0.0211	0.4551**
	(0.03506)	(0.24568)	(0.11187)	(0.07828)	(0.02145)	(0.02431)
Rainy day	-0.9293*	1.3522**	-0.9695*	-0.8958**	-1.2035**	-0.6195**
	(0.42727)	(0.31772)	(0.38832)	(0.14166)	(0.06819)	(0.05985)
Observations	303,760	800,867	801,488	6,486,612	3,697,009	6,312,300
R-squared	0.266	0.162	0.144	0.023	0.126	0.188
Route FEs	84	314	314	1,806	1,806	1,808

Note: Outcome is daily BART ridership per route; the treatment is an additional day of ride-hailing availability. The estimates parallel column (3) of Table 2, which assumes a 2-year adoption period. We estimate each group's results separately. Robust standard errors clustered by route; ** p<0.01, * p<0.05.

effects of ride-hailing. Second, BART forecasts ridership and provides their monthly goals (data.bart.gov/dataset/customer-ridership). Actual ridership has been lower than they projected for the last several years, indicating an outside and unaccounted shock, such as ride-hailing. In addition, we assess the schedule changes over the decade and find little evidence of reduced supply. Third, the results-by-group are distinct and intuitive; meaning that an unobserved trend would have to affect BART market segments in these specific ways, which is unlikely. Finally, the previous section provides additional evidence that ride-hailing substitutes for public transit, indicating plausible causal mechanisms for the long-run loss in ridership.

5 Costs of transit riders switching to ride-hailing

Evidence shows that *Uber*X and *Lyft* reduce BART ridership in the San Francisco Bay Area. As consumers are choosing ride-hailing over high-occupancy public transit, we now consider two categories of impacts: a decrease in BART's fare revenue and several negative externalities from the additional vehicle miles. The externalities include social costs from pollution, increased travel times, and auto-related collisions. We first determine average values for several parameters: BART fares, the mileage of BART trips, the occupancy of riders in ride-hailing vehicles, and the social costs per mile. We then convert change in BART ridership to dollar values. We calculate separate totals for the long-run daily trend and the short-run hourly effects. We then discuss the connection between these.

We use 2018 data as our base year and covert dollar values from other years. The average 2018 BART fare was \$4.[10] To calculate the social costs, we need an estimate of additional vehicle miles traveled (VMT), which requires assumptions about their distance of travel and how many passengers are in each ride-hailing vehicle. The average BART trip distance, 14.8 miles, is a good proxy for distance per trip.[11] To provide a range of costs, we assume either 10 or 20 miles per trip. These distance measures are conservative: by ignoring the travel between the origin and destination and entry and exit BART stations, we underestimate the total trip length. The occupancy rate for San Francisco, from Castiglione et al. (2016),

[10] See 2019 Fact Sheet, https://www.bart.gov/sites/default/files/docs/2019%20BARTFacts2019%20FINAL.pdf, accessed January 2022.
[11] *Ibid.*

is 1.66 passengers per vehicle.

We use two approaches to determine the values of social costs per VMT: (1) Parry et al. (2007) provides values for four impacts, carbon dioxide (CO_2) pollution, local pollution, congestion, and traffic collisions. (2) We collect information that is aligned with our study period, and specific to the three countires on the Bay Area, to determine alternative values for each impact. Our methods are as follows. For pollution cost per VMT, we use emission cost per metric ton and pollutant grams per mile.[12] To calculate the average Bay Area congestion cost per VMT, for each year from 2013 to 2018, we divide reported annual congestion cost in 2018$ by total annual VMT in the three counties BART operates. We then average the congestion cost per VMT across the six years ride-hailing available in the Bay Area. We calculate the collision cost as the rate of injury per VMT weighted by the probability and cost of injury type.[13] The average costs for congestion and collisions further the underestimation of the impact of the marginal vehicle because both these impacts rise in marginal cost per vehicle mile added. In sum, the average social cost per additional vehicle miles traveled is \$0.150 to \$0.574; all values in Table 4. Ours are higher than in Parry et al. (2007) because they reflect contemporary costs and pertain to the populous and congested region in which BART operates.

From Column 1 of Table 2, our results show that ride-hailing induces an annual loss of 5,529,943 trips. Thus, the estimated lost BART revenue resulting from ride-hailing is about \$22.1 million year-over-year. By 2018, we estimate a loss of \$132.7 million. These values are underestimates to the extent that transit consumers who pay higher fares are more likely to substitute to ride-hailing. For comparison, we project a counterfactual 2018 revenue of \$536.1 to \$581.8 million and BART's operating budget for the same year was \$920.6 million.[14] The lost revenue is a private transfer, from BART to the ride-hailing companies and drivers. Moreover, we acknowledge that private welfare increases because these consumers reveal their preference for ride-hailing over BART. In fact, Cohen et al. (2016) estimate consumer surplus using *Uber*X surge-price data for individual trips; for the four cities with largest markets in 2015; they find a valuation of \$2.9 billion.

[12] "benefit-cost-analysis-guidance-2018.pdf," at www.transportation.gov and "Motor Vehicle Emission Simulator" at www.epa.gov/moves/latest-version-motor-vehicle-emission-simulator-moves, accessed March 2021.

[13] "2015 Motor Vehicle Crashes: Overview" at crashstats.nhtsa.dot.gov and "Tiger Benefit-Cost Analysis (BCA) Resource Guide" at www.transportation.gov, accessed March 2021.

[14] See https://www.bart.gov/sites/default/files/docs/June18FactSheet_v1.pdf.

Table 4. Social costs of additional ride-hailing trips: Average year-over-year trend

	$/VMT		**Total Costs**		
Impact	Parry et al. (2007)	Authors' Calculations	Low	Moderate	High
CO_2 Pollution	$0.004	$0.017	$291,175	$574,657	$1,149,314
Local Pollution	$0.029	$0.005	$1,941,167	$165,980	$331,960
Congestion	$0.05	$0.433	$4,852,919	$14,418,335	$28,836,670
Collisions	$0.044	$0.109	$2,911,751	$3,632,317	$7,264,634
Sum	$0.150	$0.574	$9,997,012	$18,791,289	$37,582,578

Note: Values in 2018$. Derivations of parameters, methods, and ranges described in main text.

We monetize the year-over-year social costs using estimates of the costs per VMT, a standard benefits-transfer approach. The change in BART ridership combined with ride-hailing occupancy and distance per trip provides a range of 33,312,910 to 66,625,819 additional VMT induced by the availability of ride-hailing. Table 4 provides the year-over-year social costs. 'Low' uses the low VMT estimate and costs from Parry et al. (2007); 'Moderate' uses the low VMT estimate and our calculated costs; and 'High' column uses the high VMT estimate and our own costs. We find that total negative externality costs increase year over year by $10 to $37.6 million annually.

We now calculate costs based on our hourly difference-in-differences estimates. We focus on the two factors with the largest impacts on ridership: temperature and congestion.[15] We first find the weighted-average change in ridership over all the binned estimates, based on Figures 3 and 7. Then we multiply by the average number of system-wide operational hours per day, inferring an average daily loss of 30,864 riders due to congestion and 66,586 riders due to temperature.

Using these values, BART is potentially losing up to $248,000 per day in fare revenue due to a preference for ride-hailing over BART when temperatures are uncomfortable or ride-hailing is faster. We translate ridership into additional VMT using these ridership changes, the occupancy rate of 1.66, and the same range of 10 to 20 additional VMT per ride-hailing trip. Table 5 shows the social costs from our short-run analysis. As above, 'Moderate' uses the low VMT and 'High' uses the high VMT estimate; both apply our calculations of

[15] We disregard the short-run results from rain and AM-PM commuters as these are small in both magnitude and duration.

cost/VMT. The daily sum of impacts is — $103,000 to $207,000 from congestion shocks and $230,000 to $461,000 from temperature shocks.

Table 5. Social costs of additional ride-hailing trips: Average daily values due to hourly congestion and temperature fluctuations

Impact	**Authors' $/VMT**	**Percent /Impact**	**Congestion Costs** Moderate	High	**Temperature Costs** Moderate	High
CO_2 Pollution	$0.017	2.96%	$3,202	$6,405	$6,909	$13,818
Local Pollution	$0.005	0.87%	$925	$1,850	$1,996	$3,991
Congestion	$0.443	77.18%	$82,446	$164,892	$177,866	$355,732
Collisions	$0.109	18.99%	$20,242	$40,485	$43,670	$87,341
Sum	$0.574	100%	$106,816	$213,632	$230,441	$460,882

Note: Values in 2018$. Derivations of parameters, methods, and ranges described in main text.

Combining the temperature and congestion ridership losses is challenging in that the two impacts interact. We opt to use the temperature costs to estimate the total average daily costs since they better capture simultaneous temperature and congestion impacts that the congestion cost. Because congestion is highest during commute hours when demand is most inelastic, the congestion cost is less sensitive to simultaneous variations in temperature. It is more common to experience heavy congestion during bad weather. For example, rain affects congestion because more people drive, rather than take public transit and drive worse. As a conservative measure of short-run impacts, we use the lower value of average daily temperature costs, multiplied by 365 days, to obtain a perpetual average cost per year: $84 million.

These changes in hourly and daily ridership occur within the downward annual trend. Therefore we cannot simply add the long and short-run costs together. The daily fluctuations in ridership — and respective costs — are four times larger than the year-over-year losses. We can surmise that congestion and temperature displace numerous transit riders temporarily, yet about 80 percent of these passengers return to BART. We add the year-over-year 'moderate' value of $19 million to account for the long-run trend. Given our calculations rely on many assumptions, we refrain from an exact figure of total social costs, but a our measure is on the order of $103 million dollars in 2013 growing to $197 million in 2018.

6 Discussion

We are unaware of other studies that can discern whether ride-hailing is a complement or substitute at the metropolitan level, hourly and daily. We are the first to distinguish outcomes for distinct types of riders — commuters, airport goers, and recreational travelers. Previous studies reach conflicting conclusions about complementarity or substitution; some reasons are use of coarse scales of aggregation with differing identification strategies and time spans. A more fundamental reason is that different municipalities have differing responses to ride-hailing. Furthermore, we assess several reasons for riders' switching between public transit and ride-hailing. Public transit authorities and municipalities require these finer details for their decision making. Thus, we create a template for others to replicate our approach and find results specific to their location.

We provide methods and results for two timescales. The short-run approach captures hourly fluctuations. Its advantage is discerning the mechanisms by which ride-hailing causes declines in ridership. We focus on the two major aspects that may tip the transit riders toward ride-hailing: more protection from weather and decreased travel time. Long-run results compare time-series trends, before and during the availability of ride-hailing and suggest how the hourly exchange between BART and rail-hailing impact public transit ridership at the annual level. This gives a broad picture of aspects that strongly influence ridership, including how ride-hailing availability affects daily transit.

We showcase our methods using data from the San Francisco Bay Area. We find hourly substitution: BART users temporarily deviate from public transit in response to worsening of weather, diminished daylight, or improved travel speeds, with significant declines in ridership once ride-hailing is available. A majority return to public transit when these short-term conditions improve, but some seem to habituate to using ride-hailing, and over time this likely contributes to the long-run ridership decline. This leads to a permanent loss of 5.5 million Bay Area Rapid Transit trips, on average, for each additional year of ride-hailing availability. The decline occurs despite growth in population and employment opportunities in the city center. Of course, unobservable trends through time or space or both may undermine our findings. A possible example is differential surge pricing, practiced by ride-hailing companies, which is not captured by route and time fixed effects. However, our results by rider-group bolster our confidence based on the patterns, such as

small elasticities for commuters and high elasticities for recreational and airport ridership.

Further, the preponderance of related facts and literature support our findings. BART ridership has been significantly lower than forecasts by the transit authority, suggesting their model is not accounting for some factors. The SF Mobility Report indicates that San Francisco residents are 'driving their own cars less, but multiple indicators show that overall driving and congestion is growing,' over the past decade, vehicle speeds declined by 23 percent.[16] Several recent papers find that ride-hailing causes an increase in vehicle miles, conditional on other growth factors (Erhardt et al., 2019; Henao and Marshall, 2019; Tirachini and Gomez-Lobo, 2020); Tirachini (2019) provides a comprehensive overview. The increase implies that ride-hailing induces current drivers to take additional trips or transit riders to switch. In particular, Rayle et al. (2016) surveys ride-hailing passengers in central San Francisco, where over 30 percent of participants state they chose ride-hailing over their next best choice of public transit. Similarly, Schaller (2021) assesses consumers in four major U.S. cities, including San Francisco, concluding that VMT increases due to empty ride-hailing vehicles searching for their next customer, but moreover, because consumers shift from public transit.

7 Conclusions

Uber and *Lyft* have been enormously successful in creating an app-based technology that matches passengers with drivers, for a taxi-like service (Castiglione et al., 2016; Cramer and Krueger, 2016). In addition to improving informational efficiencies for this market, ride-hailing offers other private benefits. For the drivers, ride-share gigs offer flexible compensation without the commitments of traditional employment or taxi-leasing (Angrist et al., 2021; Chen et al., 2020, 2019). For the passengers, ride-hailing increases access to areas not served by transit systems, arrives on-demand, and can offer more comfort and safety than public transit — research shows the service increases personal mobility and consumer surplus (Christensen and Osman, 2021; Cohen et al., 2016). As these emergent technologies evolve, transport as a 'service' will become an even larger share, affecting demand for public transport and thus its provision and operations (Hörcher and Tirachini,

[16] www.sfmta.com/sites/default/files/reports-and-documents/2019/01/mobility_report_accessible_final.pdf, accessed 04/26/2020).

2021; Webb, 2019).

Concurrently, public transit ridership across the U.S. has fallen significantly. Using data for San Francisco, we speculate that the 2019 counterfactual ridership would have been 11.2 to 21 percent higher.[17] Causes stem from numerous factors (Graehler et al., 2019; Grisby et al., 2018; Manville et al., 2018b).[18] Is ride-hailing a factor that displaces public transit? Initial studies find mixed evidence, whereas, more and more recent evidence support our findings and attribute ride-hailing as part of the transit decline (Erhardt et al., 2021; Hall et al., 2018; Nelson and Sadowsky, 2018; Tirachini, 2019). Lower ridership has several consequences. One is reduction of fare revenue, which hinders agencies' functionality, such as maintaining existing infrastructure and affording new capital investments. We project that BART fare revenue is 10.3 to 17.4 percent lower relative to the counterfactual. Another repercussion is more traffic due to additional ride-hailing in lieu of mass-transit. Although pooled ride-hailing options exist, Tirachini and Gomez-Lobo (2020) find that the average ride-hailing occupancy rate fails to offset increases in vehicle miles traveled, leading to more congestion.

More traffic and its congestion are wasteful, causing a loss of personal-time, imposed on all drivers, and further amplifying the other external costs to society. We value travel-time costs using parameters from San Francisco, obtaining the opportunity cost of \$0.443 per VMT — 77 percent of social impacts. Recent SF-specific modeling from Erhardt et al. (2019) indicates that ride-hailing increased congestion delays the metro area by three-fold, compared the counterfactual without them. Anderson (2014) establishes that a shutdown of Los Angeles's metro caused a dramatic increase in congestion costs. The empirical contrapositive is also true: Gu et al. (2021) find that new subway lines reduce roadway congestion in China. We convert their value, \$0.10/vehicle conditional on a 3-percent improvement in traffic speed, using U.S. time values and the decline in speed based on our data, ranging from 0.25 to 0.5 percent; this external-cost calculation gives \$9.5 to 35.3 million per year — strikingly similar to our findings above. Furthermore, increased traffic raises the rate of collisions, which have collateral property damage, personal injuries, and fatalities. Barrios et al. (2020) demonstrate that more ride-hailing activity leads to more quarterly fatalities for U.S. cities; they reason that ride-hailing increases the roving in

[17] Values are from unconditional linear projection of Figure 1, using 2011 to 2014 data.

[18] A 2018 Economist article blames "remote working, Uber, cheap car loans and the internet" www.economist.com, accessed 06/12/2021.

search of passengers and the driving of unfamiliar roads, among other factors, which lead to more collisions. Fatalities are tragic, which they capture using the value of statistical life, finding an annual cost per capita of $15 to $40. For the San Francisco metro area, this is $49 to $133 million. Thus, the Bay Area 2018 cost of collisions is around $40 million — a reasonable value as ours combines property damage and injuries as well as fatalities. And another consequence, though relatively small, is environmental damage: at less than 4 percent of the social impacts, the pollution cost for both local emissions and CO_2 is $0.22/VMT.

These papers about impacts, coupled with our findings, provide a corollary: a robust public mass-transit system is critical in mitigating the social costs of driving. Municipalities and agencies need specificity to create targeted policies when addressing crowding out by ride-hailing. Our results lack external validity, as each location is heterogeneous in the structure of their public transit and in geographical, socio-demographic, and temporal factors. Instead, we provide a methodological tool. Municipalities and agencies can adapt and apply our framework, which requires only public data to understand their own regions' dynamics. It is imperative that these public entities improve data collection of more detailed measurements to measure the impacts of ride-hailing and respond appropriately.

How else can public transit adapt as ride-hailing transforms the transportation industry? Unlike private services, the focus of public transit authorities is on total societal welfare and distributional equity given a budget constraint. Alternatives, like ride-hailing, place pressure on budgets making it increasingly difficult for public transit agencies to operate. Rather than try to compete across the entire travel demand market, it may be more strategic for public transit agencies to increase attention to the segments they serve best. However, devoting more resources to high performing routes may then require cutting service in areas with low-income or transit dependent populations.

In parallel, government policies can support public transit authorities and regulate with ride-hailing companies to mitigate the social costs. Governments subsidize public transit, which encourages usage, and moreover, is net beneficial (Parry and Small, 2009). In particular, subsidies can focus on routes that diverts drivers off the congested roads. Through public-private partnerships, governments hope to create complementarity by paying for

ride-hailing trips to and from public transit hub.[19] For regulation, a first best solution is a vehicle miles tax, or other congestion pricing, thus charging with ride-hailing companies at the cost of their marginal impact. Our social costs provide an estimation of the Pigouvian tax, at $0.57 per mile. Unfortunately, Dudley et al. (2017) demonstrate how adept these companies have been at circumnavigating the congestion pricing in London. On the other hand, Hanna et al. (2017) show lanes for high-occupancy vehicles are another effective tool for mitigating traffic. Thus, as a positive incentive in combination with a tax policy, pooled ride-hailing could use such lanes or forgo the tax. Rather than focus on VMT reduction, California recently mandated that 90 percent of ride-hailing fleets must be electric vehicles (EV) by 2030, to mitigate the environmental costs.[20] This California policy overlooks the largest cost of ride-hailing availability — congestion and collisions are 96.2 percent of social cost. As riders exchange high-occupancy modes for ride-hailing, social costs are rising, thus policies reducing vehicles miles are more crucial.

[19] See www.apta.com, accessed 07/21/21.
[20] See www.reuters.com, accessed 06/20/2021.

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