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Subsidized ridesourcing for the first/last mile: how valuable for whom?

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The first/last mile is a long known deterrent to public transportation use, yet difficult to solve with fixed route transit. Many transit agencies are exploring partnerships with ridesourcing companies to offer subsidized feeder services. Ridership, however, has been surprisingly low. We explore two conceptual explanations. First, ridesourcing fares are found to exceed travel time savings for all distances below 1 mile and annual household incomes below USD 30,000 (i.e., the majority of US bus-using households). Subsidies are thus necessary, yet common schemes (flat fees, flat value or percentage discounts) are inequitable as they particularly benefit high-income households (thus miss their main target group). Second, the disutility of the additional transfer ('transfer penalty') and wait times exceed travel time savings assuming modest values for all distances below 0.45 miles. Subsidized ridesourcing for the first/last mile is thus not the panacea often portrayed, particularly not for short first/last miles. Where first/last miles are longer, investments in first/last mile services only might miss their purpose as the private car often remains the faster, more convenient and cheaper option. A much more holistic set of policy changes is hence required. Where transit agencies decide to proceed with first/last mile subsidies, they are advised to integrate them into existing fares (offering first/last mile rides for free) as this is the most equitable approach.

Keywords: *Autonomous taxis, First mile, Last mile, Ridesourcing, Subsidies, Transfer penalty, Value of travel time savings.*

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1. Introduction

Most transit users walk to/from the (closest) stop at the beginning or end of a trip. Depending on the actual distance, this 'first/last mile' can be a deterrent to public transportation (PT) use due to the time it takes to overcome a relatively short proportion of the trip, safety concerns and weather conditions. This is long known to transportation planners, however, it remains difficult to solve with typical fixed-route, large-capacity vehicles due to dispersed spatiotemporal demand.

Demand-responsive feeders have been suggested as a remedy to the 'first/last mile problem' in varying forms at different times (for an overview, see Chandra and Quadrifoglio, 2013). We identify three phases. First deployments in the 20th century ('phase 1') included minibuses and taxis called via landline. Technological constraints (manual routing, scheduling and dispatching) often resulted in low levels of ridership and/or high expenditures (Mageean and Nelson, 2003; Davison et al., 2014).

The dissemination of GPS-enabled smartphones, advances in routing algorithms and computing power, and regulatory voids have enabled new (cost-) efficiencies in demand-responsive transportation and led to the rise of ridesourcing companies such as Uber, Lyft and Via. Their use as first/last mile feeders ('phase 2') has often been suggested (e.g., Feigon and Murphy, 2016; Westervelt et al., 2017; Alemi and Rodier, 2018; Shaheen and Chan, 2018; Bian and Liu, 2019). Google recently implemented this feature in its Maps service (Google, 2019) and many transit agencies in US[3] and recently German[4] cities have engaged in partnerships to subsidize first/last mile rides. Interestingly, though, there appears to be a gap between expected and realized ridership, which has remained surprisingly low in several pilots despite little or zero additional costs to the user:

- The 'Go Centennial' pilot, which offered customers to/from Dry Creek light rail station in Centennial (CO) free first/last mile Lyft rides between Sep. 2015 and Jan. 2016, had an average ridership of 7.1 per day (City of Centennial, 2017). The final report concludes "ridership was lower than expected or desired" (City of Centennial, 2017, p. 54).
- The 'Direct Connect' pilot, which offered customers to/from 4 bus stations in Pinellas County (FL) a USD 5 subsidy on first/last mile Uber/Taxi rides, had an average ridership between Feb. 2016 and Aug. 2016 of "less than two per day" in phase 1 of the pilot (Murphy and Karner, 2019, p. 12). Ridership increased following expansions in subsequent phases of the pilot, yet always remained below the stated goal to reach 50 rides per day (Murphy and Karner, 2019, pp. 13, 17).
- The 'Berlkönig BC' pilot, which offered customers to/from Rudow rail station in Berlin (Germany) first/last mile Via rides for EUR 0.50 between Aug. 2019 and Oct. 2019, had an average ridership of 20 per day, which was less than 10% of the expected ridership of 250 per day (Hasselmann, 2019).

Several other first/last mile pilots have reported low ridership numbers, however without previously publishing their expectations (e.g., 'MOIA+ÜSTRA' in Hannover, Germany (Hannoversche Allgemeine Zeitung, 2019), 'GETSMART17' in Marin County, CA (Steinhauser and McGill, 2018)).

So-far, explanations for low ridership on first/last mile ridesourcing services have been related to specific implementation issues (e.g., sparse marketing, short pilot duration, small pilot area, high operational costs) (e.g., City of Centennial, 2017; Murphy and Karner, 2019; Currie and Fournier, 2020). This paper explores two conceptual explanations. For short distances, the additional transfer between the ridesourcing vehicle and the subsequent PT vehicle and its associated disutility

[3] E.g., Atlanta, Austin, Centennial, Charlotte, Chicago, Los Angeles, Pinellas County and Seattle (for an overview, see Schwieterman et al., 2018).
[4] E.g., Hamburg and Hannover.

('transfer penalty') as well as wait times (from request to pickup) could diminish perceived travel time savings. Additionally, the cost to be borne by the user might exceed the value of travel time savings (VTTS) despite a given level of subsidy in particular for low-income households. We quantify the impact of each argument first conceptually, then empirically by simulating a first/last mile service for commuting trips in three US regions that currently partner with ridesourcing companies, however, structurally differ: Seattle (Washington), Pinellas County (Florida) and Marin County (California). Note that this paper focuses on comparing the impact of transfer penalties, wait times and additional costs on perceived travel times savings and VTTS of a 'ridesourcing + PT' versus a 'walk + PT' option. Often, the 'car only' option (for whom available) remains most attractive in terms of convenience, travel costs and travel times regardless of the first/last mile access. We return to this argument in the Conclusion section of this paper and illustrate it by calculating travel times for the 'car only' option as well.

This paper makes three contributions. First, we connect three streams of research (demand-responsive feeders, transfer penalties and VTTS) that have previously remained largely detached. Second, we propose two alternative explanations for low ridership on first/last mile ridesourcing services and quantify their impact. We develop and describe a methodology that solely relies on open data, enabling transit agencies to assess the potential of first/last mile partnerships in their locality. Lessons are distilled for their suitability for three different regions and the equity implications of different subsidy schemes. Third, and perhaps most importantly, our findings can be applied to any vehicle-based first/last mile feeder service in the future, i.e. autonomous taxis ('phase 3'), challenging the frequent view that autonomous taxis could complement PT on the first/last mile (Chong et al., 2011; Liang et al., 2016; Yap et al., 2016; Scheltes and de Almeida Correia, 2017; Shen et al., 2018; Wen et al., 2018).

This paper is structured as follows. We first review the literature on transfer penalties, wait times and VTTS, explore the missing links to demand-responsive feeders and develop the conceptual argument. We then introduce our methodology to quantify the impact empirically. A short introduction of the case studies is followed by the results of our analyses. We conclude with a summary and a discussion of the implications for transportation policy and future work.

2. Literature review and theoretical reasoning

2.1 Transfers

First/last mile services cause an additional transfer between the feeder vehicle and the subsequent/previous PT vehicle. Passengers, however, generally prefer to avoid transfers due to factors such as anxiety to reach the subsequent connection, waiting times, security, activity disruption and comfort (Currie, 2005; Iseki and Taylor, 2009; Cheng, 2010). This applies in particular for first mile services as a subsequent PT connection has to be reached, while is arguable not as important for the last mile. Despite a long history of research into transfers and the associated disutility ('transfer penalty', usually quantified in minutes passengers would prefer to continue their journey to avoid a transfer) (Algers et al., 1975; Alter, 1976; Allen and DiCesare, 1976; Newell, 1979; Horowitz, 1981), this stream of research has not been systematically connected to demand-responsive feeders for the first mile. Yet, by definition, first miles tend to be short distances, thus the travel time savings using a ridesourcing vehicle is often similar to the magnitude of the transfer penalty itself.

Empirical studies investigating the *actual* size of the transfer penalty exhibit wide ranges in values. Currie (2005) provides an international review finding an average transfer penalty for bus-to-bus transfers of 22 min (ranging between 5 and 50 minutes) of in-vehicle travel time. More recently, Guo and Wilson (2011) found a transfer penalty range for subway-to-subway transfers in London of 1 to 9 minutes (differing by subway station). Arentze and Molin (2013) found an average transfer penalty for rail-to-rail transfers in the Netherlands of 12 minutes and Frei et al. (2017) found an average transfer penalty for transfers between demand-responsive shuttles of 4.9 minutes. Reasons for these wide ranges are context-sensitivity (e.g., climate, security, local amenities, type of vehicle, service frequency and reliability) (Iseki and Taylor, 2010; Guo and Wilson, 2011) and measurement scope (e.g., waiting time, walking time to the subsequent vehicle, and/or the disutility of the transfer itself) (Garcia-Martinez et al., 2018). In a recent effort to improve comparability, Garcia-Martinez et al. (2018) investigate the 'pure transfer penalty' (i.e., without walking or waiting times). Using stated-preference data in Madrid, they find the 'pure transfer penalty' to average 15.2 min.

Yan et al. (2019) are the first (and only to our knowledge) to explicitly consider the disutility of the additional transfer caused by the first/last mile service in their survey-based investigation of traveler responses to a hypothetical first/last mile ridesourcing service on the University of Michigan Ann Arbor campus. Despite finding a transfer penalty of 10.9 min in-vehicle travel time, they conclude: "when used to provide convenient last-mile connections, ridesourcing could provide a significant boost to transit". (p. 1) The apparent contradiction between average first/last mile distances/travel times and a transfer penalty of 10.9 minutes, however, remains unresolved and motivates our study.

The argument is visualized in Figure 1. First, we plot the travel time (y-values) for the feeder (black line) and walking (grey line) for distances between 0.1 and 1 mi (x-values). Walking is slower thus the line is steeper. We assume a walking speed of 3 mph and a driving speed of 20 mph. Next, we add 10 min as a hypothetical transfer penalty value to the driving line (this results in an upward shift of the black line, see dotted black line). It is important to note that transfer penalties are usually reported equivalent to in-vehicle-minutes. Wardman (2004) and Arentze and Molin (2013) have found the disutility of 1 min access walking time to be equivalent to ~2 min in-vehicle-time (i.e., travelers prefer to be driven than to walk). Thus, a transfer penalty of 10 min in-vehicle-time is equivalent to 5 min walking time. Likewise, travel times using the feeder have to be divided by 2 to be equivalent to (perceived) walking time.

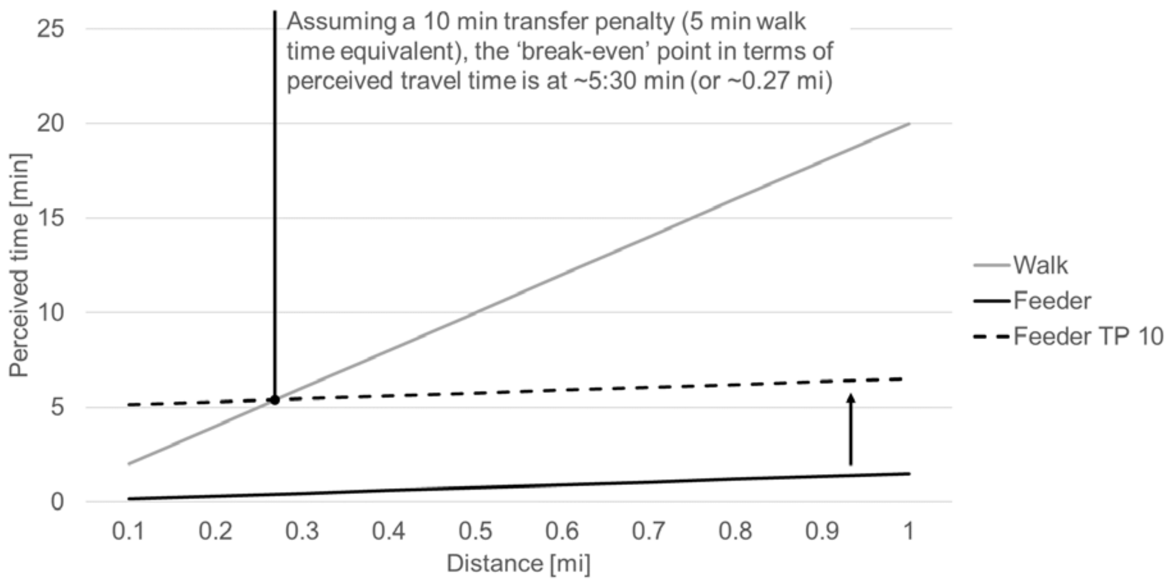

Figure 1. Travel time comparison for a first mile walk vs feeder service. Transfers are hypothesized to decrease their utility on short distances.

The resulting intersection between the walking line and the driving (incl. transfer penalty) line can be interpreted as the distance, from and beyond which a first mile feeder is (perceived) faster than walking despite the transfer penalty (here: at ~5:30 min or ~0.27 mi). The corresponding formulas for Figure 1 are:

$$\boldsymbol{time_{walk}} = \frac{\boldsymbol{distance}}{\boldsymbol{3}} * \boldsymbol{60} \tag{1}$$

$$\boldsymbol{time_{feeder}} = \frac{\frac{\boldsymbol{distance}}{\boldsymbol{20}} * \boldsymbol{60}}{\boldsymbol{2}} \tag{2}$$

$$\boldsymbol{time_{feeder\ TP\ 10}} = \frac{\frac{\boldsymbol{distance}}{\boldsymbol{20}} * \boldsymbol{60+10}}{\boldsymbol{2}} \tag{3}$$

Here, *time* corresponds to the perceived travel time [min] (equivalent to walking time) using the corresponding mode. *Distance* refers to the distance travelled [mi]. Travel time using the feeder service (including the transfer penalty) is divided by 2 to be equivalent to (perceived) walking time.

2.2 Wait times

Wait times for the ridesourcing service (from request to pick up) further decrease potential travel time savings and apply equally for first and last mile services. Wang and Mu (2018) find an average wait time for Uber of 6 min (ranging between 3 to 10 min) for Atlanta. Arentze and Molin (2013) and Wardman (2001) have found the disutility of 1 min access walking time to be equivalent to ~1.5 min wait time. Thus, an additional wait time of 3 min is equivalent to 2 min walking time.

We convert different wait times (3, 5, 10 min) to walk time equivalents and add them to the feeder line representing our first mile ridesourcing service (Feeder TP 10) in Figure 1. Figure 2 shows the result. Here, we observe a further upward shifts of the original feeder line ('Feeder TP 10'). As a result, the 'break-even' point in terms of perceived travel time further shifts upwards when considering the additional wait times. For example: when we consider a transfer penalty of 10 min (5 min walk time equivalents) and an additional wait time of 5 min (3:20 min walk time equivalents), the first mile feeder is (perceived) faster than walking from and beyond a distance of ~0.45 mi (or ~9 min walk time). In other words, below 0.45 mi walking is perceived as the faster option.

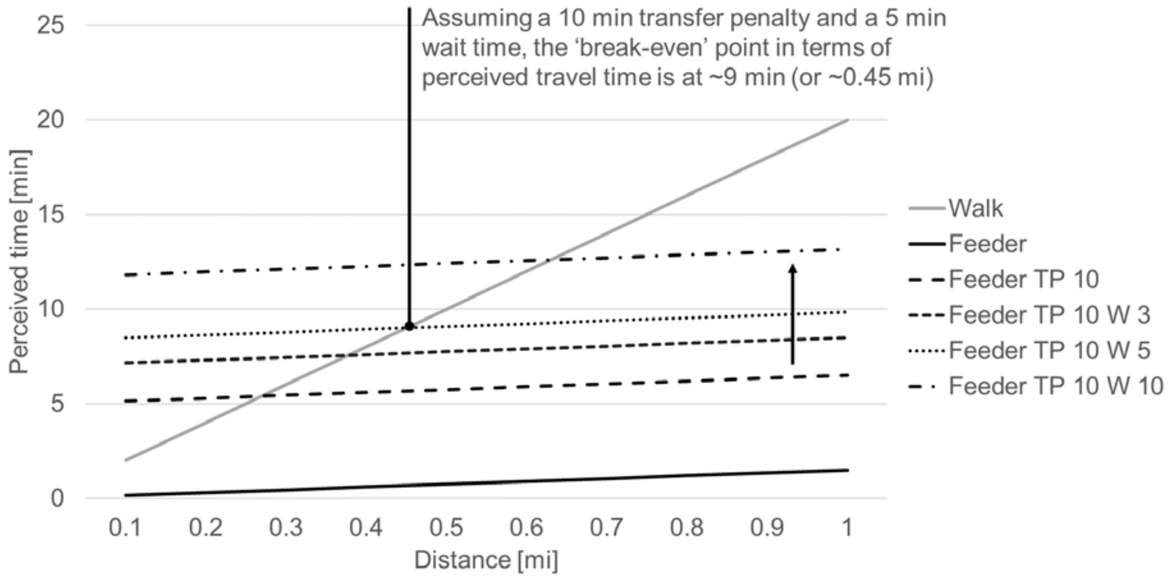

Figure 2. Travel time comparison for a first mile walk vs feeder service. Wait times and transfers are hypothesized to decrease the utility of feeder services on short distances.

The corresponding *additional* formula for Figure 2 is:

$$\boldsymbol{time}_{feeder\ TP\ 10\ W\ X} = \frac{\frac{distance}{20} * 60 + 10}{2} + \frac{X}{1.5} \quad (4)$$

We refer to our notion remarks for formulas *(1)* to *(3)*. Additionally, *X* refers to the additional wait time [min], which is divided by 1.5 to be equivalent to (perceived) walking time.

2.3 Costs

First/last mile services may cause additional costs for the user depending on the subsidy scheme. Given the high share of transit-using households in the US with an income of less than USD 15,000 (30% of bus-using households (Clark, 2017)), additional costs may be another barrier to the use of demand-responsive feeders for the first/last mile.

Current first/last mile ridesourcing subsidy schemes broadly fall into four categories (as of July 2019):

- Most transit agencies offer a USD 4-5 ‘flat value discount’ on the Uber/Lyft/Taxi fare (Charlotte, Marin County, Pinellas County). However, in some regions (e.g., Pinellas County), Uber’s minimum ride price of USD ~6 leaves at least an USD ~1 surcharge even for the shortest distances.
- Seattle integrates its three first/last mile providers into their ORCA card based PT pricing scheme, offering first/last mile connections (or subsequent/previous PT rides) for free (‘full fare integration’). PT standard trip fares apply (2.75 for adults, 1.5 for youths). First/last mile services were offered for free (without PT fare integration) in Centennial (CO) and Austin (TX).
- Los Angeles (CA) and Hannover (Germany) offer first/last mile rides for flat fares of USD 1.75 (with a TAP card) and EUR 3, respectively, with free rides for low-income subsidy program eligible in Los Angeles and a surcharge of USD 2 without a TAP card.
- Phoenix, AZ, offered a 20% discount on the total fare of first/last mile rides.

How do the remaining surcharges compare to the value of travel time savings, and how does this depend on income?

While a comprehensive review of the value of travel time savings literature would exceed the scope of this paper, we focus on reported values for US transit rides. Since 1997, the US Department of Transportation (US DOT) publishes its ‘Departmental Guidance for the Valuation of Travel Time in Economic Analysis’. Since 2011, the US DOT calculates the VTTS for personal travel (including commuting) at 50% of the hourly mean household income for in-vehicle-time savings and at 100% of the hourly mean household income for walking time savings (Belenky, 2011; Timothy, 2016). This value follows the recommendations developed by Concas and Kolpakov (2009) and Zhang et al. (2005) for the US and Canada and is within the range found by Zamparini and Reggiani (2007) in their meta-study for commuting trips in Europe, North America and Australia. While the approach to consider a single VTTS value for transportation appraisals has recently been criticized for negating increasingly flexible work practices, variations in income and interpretations of travel time (Hensher, 2019), it is widely used in practice and (still) recommended by the US DOT.

In 2015, the recommended VTTS/h value was USD 13.60 (Timothy, 2016), or USD ~2.3 for 10 minutes. Given minimum Uber fares of USD 5 (Hall et al., 2018), it is thus natural to question whether surcharges exceed VTTS on the first/last mile, and how this depends on distance, income and subsidy scheme.

Figure 3 visualizes this argument. We plot the difference of ridesourcing trip costs (using Lyft rates for Seattle without surge pricing, Lyft 2019a) and VTTS (y-values) for trips between 0.1 and 2 mi (x-values) at 4 different VTTS/h rates dependent on the annual household income. VTTS/h is calculated using the US DOT recommendations outlined above for a 2018 US mean household income of USD 61,937 and scaled to USD 15,000, 30,000, 60,000 and 90,000 using the square root relationship suggested by Waters II (1993)

$$\boldsymbol{VTTS_Y} = \sqrt{\boldsymbol{Y}/_{\bar{\boldsymbol{Y}}}} * \overline{\boldsymbol{VTTS}} \tag{5}$$

where the VTTS for a specific household income Y is calculated using the mean household income $\bar{Y}$ and the VTTS for the mean household income $\overline{VTTS}$. $\overline{VTTS}$ is calculated using 50% of the mean hourly household income (i.e., the 2018 mean yearly household income of USD 61,937 divided by the yearly working hours of 2080)[5].

$$\overline{\boldsymbol{VTTS}} = \boldsymbol{0.5} * \frac{\boldsymbol{61937}}{\boldsymbol{2080}} = \boldsymbol{14.89} \tag{6}$$

Resulting VTTS/h values for the four income levels are USD 7.3, 10.4, 14.7 and 17.9, respectively. These values have to be multiplied by two to be applicable to walking time replaced by the (perceived as more convenient) ridesourcing vehicle (Timothy, 2016).

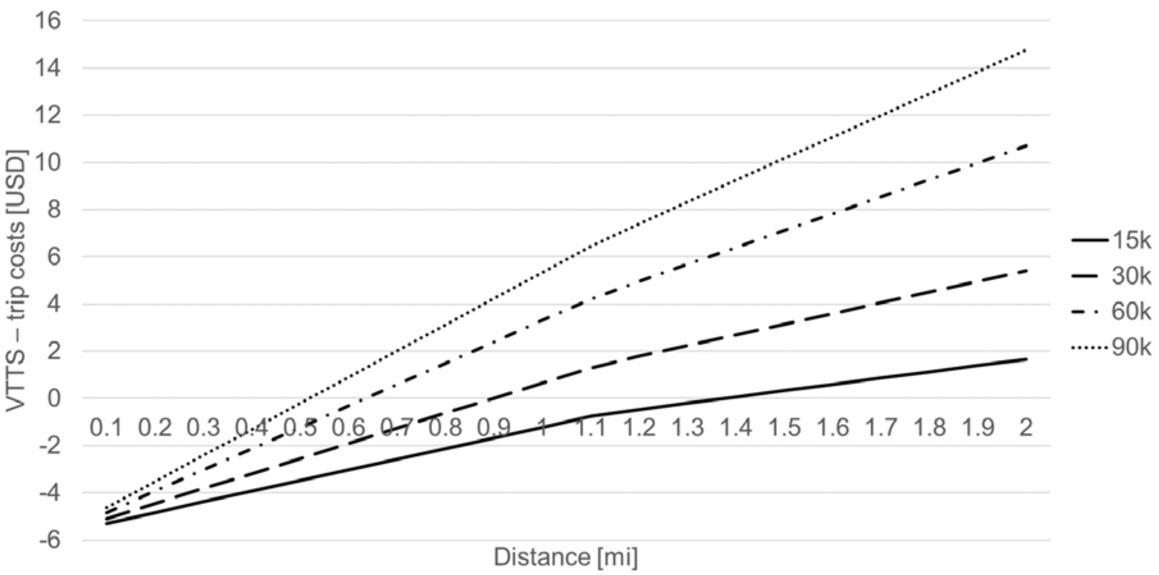

Figure 3. Difference between value of travel time savings and ridesourcing costs at different household incomes. Negative values are hypothesized to deter from the use of ridesourcing as a first/last mile feeder.

As argued above, the VTTS are lower than trip costs for any distance below ~1 mi for households with an annual income of USD 30,000 and below. Even at a yearly household income of USD 90,000, the VTTS only surpass trip costs for distances greater than ~0.55 mi. We see a slight change in slope for all curves at ~0.9 mi as it is here that the minimum trip costs of USD 5.74 (USD 3.5 minimum fare + USD 2 service fee + USD 0.24 Seattle city fee) are reached (and subsequently surpassed). The corresponding formulas for Figure 3 (exemplary for a household with USD 15,000 yearly household income) are:

$$\boldsymbol{y_{15k}} = \boldsymbol{\Delta traveltime} * \boldsymbol{VTTS_{15k}} - \boldsymbol{tripcosts} \tag{7}$$

[5] We calculate the number of yearly working hours by taking the number of yearly working days (260) and multiplying it by 8 working hours.

$$\boldsymbol{\Delta traveltime = time_{walk} - time_{feeder}} \tag{8}$$

$$\boldsymbol{VTTS_{15k} = \sqrt{\frac{15000}{61937}} * \overline{VTTS} * 2} \tag{9}$$

$$\boldsymbol{tripcosts = MAX\left\{1.48 * distance + 0.25 * \frac{distance}{20} * 60 + 1.42\,, 3.5\right\} + 0.24 + 2} \tag{10}$$

Here, $time_{walk}$ refers to equation (1) and $time_{feeder}$ to equation (2). The different elements of the Lyft rate (*tripcosts)* for Seattle (Lyft 2019a) are the maximum between (1.48 USD/mi + 0.25 USD/min + 1.42 USD base fare) and the 3.5 USD minimum fare, an additional 2 USD service fee and a 0.24 USD Seattle city fee.

In this section, we illustrated our arguments assuming equal distances for walking and driving on the first/last mile. As this assumption is clearly unrealistic (e.g., you might cut through a park to save time walking or you might have to take a detour to the next pedestrian bridge), we proceed with an empirical evaluation using three case studies.

3. Methodology

We calculate first/last mile travel time savings and VTTS - cost differences for commuting trips in three different regions that currently operate first/last mile pilots (for a short introduction, see next section).

Block-group level origin-destination (OD) commuting trip information is obtained from the 2015 US Census Origin-Destination Employment Statistics (US Census Bureau, 2019a). This includes 137,954 OD pairs for Seattle, 103,216 OD pairs for Pinellas County and 11,605 OD pairs for Marin County. For each OD pair, we obtain PT travel times including access/egress walking times (Alternative A) and wait times during the morning peak using the Google Directions API for R. We extract the coordinates of the first and last PT station for each trip and (again using the Google Directions API) obtain alternative driving travel times for the first/last mile (i.e., from the origin to the first PT station, and from the last PT station to the destination) where distances are larger than 0.25 mi (common walking distance to PT, see Daniels and Mulley, 2013 and Hess, 2012). Where available, we next substitute the original *access* walking times with the newly obtained driving times (Alternative B, 'first mile ridesourcing'), the original *egress* walking times with driving times (Alternative C, 'last mile ridesourcing') or both (Alternative D, 'first/last mile ridesourcing'). Figure 4 visualizes the different alternatives.

		Access to transit ('first mile')	
		Walking	**Ridesourcing**
Egress from transit ('last mile')	**Walking**	Alternative A	Alternative B
	Ridesourcing	Alternative C	Alternative D

Figure 4. Alternative access/egress combinations for which travel times are compared.

For each Alternative A-D, we calculate the total travel time in walk time equivalents as described in Section 2.1. We proceed by testing the impact of a 5 min transfer penalty (walk time equivalent of 10 min in-vehicle-time) for a first mile transfer (i.e., from ridesourcing to transit) and 2, 3:20, 6:40 min wait time (walk time equivalents for 3, 5, 10 min wait time) for each first/last mile transfer (i.e., from ridesourcing to transit *and* from transit to ridesourcing) on total travel time savings. We report the aggregated sum of travel time differences between our default Alternative A (access/egress walk) and the fastest Alternative B-D using ridesourcing for the first and/or last mile under different wait time/transfer penalty assumptions.

For our cost comparison, we proceed as outlined in Section 2.3: we calculate ridesourcing trip costs using publicly available information from Lyft in Seattle (Lyft, 2019a) and the San Francisco Bay Area (Lyft, 2019b) and a secondary source for the Tampa Bay Area (Estimate Fares, 2019), where official information from Lyft was unavailable. Fare structures consist of a base fare, costs per mile and minute, a maximum/minimum fare, service and city fees (see Formula (10)). For each first/last mile trip, we calculate and compare VTTS (at four different annual household income levels) and ridesourcing prices in four common set-ups: without subsidies, with a USD 5 flat value discount, with a 20% fare reduction and at a flat fee of USD 1.75.

4. Case studies

We apply our methodology to three case studies that currently pilot first/last mile ridesourcing partnerships, however, structurally differ in terms of number and size of population centers, overall population density and transportation availability and use: Pinellas County (Florida), Marin County (California) and Seattle (Washington). This way, we intend to test the impact of our hypotheses in very different US regions where PT agencies have decided to partner with ridesourcing firms. This section provides an overview of each region including a brief description of the respective first/last mile service. Data is extracted from the American FactFinder (US Census Bureau, 2019b) and the National Transit Database (FTA, 2019) where not otherwise noted. Table 1 summarizes the case studies along a number of regional characteristics.

4.1 Pinellas County

Pinellas County, FL has an estimated population of 975,280 (2018). The overall population density is 3,559 inh./sq. mi. and its largest city is St. Petersburg with 265,098 inh. (2018). Pinellas County has a median age of 47.6 (US median: 37.8) and a median household income of USD 48,968 (US median: 57,652) (2017).

The large majority commutes to work driving alone (79.1%) with very few using PT (1.8%) (2017). Pinellas Suncoast Transit Authority (PSTA) reported 12.2 annual unlinked trips per capita within the service area and operates (demand-responsive and fixed-line) busses (2017).

PSTA’s first/last mile partnership with Uber (‘Direct Connect’) was reportedly the first of its kind (Murphy and Karner, 2019). Having evolved through three stages since its foundation in Feb. 2016, it now offers a subsidy of USD 5 for Uber and taxi rides to/from 24 bus stations. When the first author visited Pinellas County in January 2019, most bus stations were simple road-side bus stops without specific parking/kiss and ride zones or bike stands to encourage access modes other than walking. Some buses had bike racks, but these were seldomly occupied. Roads were wide (typically 2-3 lanes each direction) and usually had sidewalks to access bus stations.

4.2 Marin County

Marin County, CA (San Francisco Bay Area) has an estimated population of 259,666 (2018) and is by far the largest region (520 sq. mi. which compares to 274 sq. mi. for Pinellas County and 84 sq. mi. for Seattle). The overall population density is low (499 inh./sq. mi. or one seventh the density of Pinellas County) as large parts of the population are focused in the small area of Sausalito/San Rafael and large parts of the county are uninhabited (national parks and other protected land). San Rafael is the largest city in Marin County with 58,704 inh. (2018). Marin County has a median age of 46.1 and a median household income of USD 104,703 (2017), more than twice as much as Pinellas County, ranking as 13th richest county by median household income in 2016.

The majority commutes to work driving alone (65.3%) (2017). The percentage of commuters using PT (9.8%) is more than five times higher than in Pinellas County (1.8%) despite a similar reported number of 11.7 annual unlinked trips per capita (2017). This suggests a different PT usage (more regular commuters and less infrequent users) or different work realities (more part-time commuters). Marin Transit operates (demand-responsive and fixed-line) busses (2017). Sonoma-Marin Area Rail Transit (SMART) runs an additional commuter rail between Sonoma and Marin counties which carried an additional 772,961 passengers in fiscal year 2017/2018 (SMART, 2018). In general, transportation flows in the region include a large share of inter-county trips to/from neighboring counties (Sonoma and San Francisco in particular) which shows that despite of its low population density, the county is part of one the largest metro areas in the USA (San Francisco Bay Area).

SMART's first/last mile partnership with Lyft ('GETSMART17') started in Sep. 2017 and offers a subsidy of USD 5 for Lyft rides to/from 4 rail stations (note that our subsequent analyses focus on the Marin County Transit District). These stations often include bike stands and dedicated parking zones.

4.3 *Seattle*

Seattle is the largest city in the state of Washington and has an estimated population of 744,955 (2018). The urban core is very dense, which makes Seattle very different from the other two regions analyzed. Its overall population density is 8,883 inh./sq. mi. (more than 2x/17x as dense as Pinellas County/Marin County, respectively) (2018). Seattle has a median age of 35.7 and a median household income of USD 79,565 (2017).

The majority commutes to work driving alone (48.8%), however a substantial share uses PT (21.4%) or walks (10.2%). Seattle is home to three transit organizations: King County Metro, Seattle Center Monorail Transit and Central Puget Sound Regional Transit Authority. In sum, they reported 77.85 annual unlinked trips p.c. within their respective service areas (~7 times as many as in Pinellas and Marin counties) on a variety of vehicles (e.g., light rail, commuter rail, monorail, busses, trolleybuses) (2017).

King County Metro started its first/last mile partnership with three different providers in three different areas in Oct. 2018. Fares are integrated into PT pricing: customers who pay with the ORCA card can transfer to a subsequent PT vehicle for free. Some of its light rail stations include bike stands and dedicated parking zones while bus stops are often simple road-side signs with a bench.

Table 1. Summary of case studies and regional characteristics.

Indicator	Unit	Pinellas County	Marin County	Seattle
Population	Inhabitants	975,280	259,666	744,955
in largest city	%	27.2	22.6	NA
Area	sq. mi	274	520	84
Population density	Inh./sq. mi	3,559	499	8,883
Median household income	USD	48,968	104,703	79,565
Median age	Years	47.6	46.1	35.7
Commute mode share				
Drove alone	%	79.1	65.3	48.8
Carpooled	%	7.8	8.1	7.6
Public transportation	%	1.8	9.8	21.4
Walked	%	1.6	3.7	10.2
Other	%	3.0	2.4	5.0
Worked at home	%	6.7	10.7	7.0
Annual unlinked trips per capita	Count	12.1	11.7	77.9

5. Results

In this section, we report on the results of our analyses. Where averages are reported, these are weighted by number of OD trips.

In Section 2, we noted that assuming equal distances for walking and driving on the first/last mile is unrealistic (e.g., you might cut through a park to save time walking or you might have to take a detour to the next pedestrian bridge), which is why our theoretical argument has to be tested empirically. How long are first/last miles in our three regions and how do distances compare for different access/egress modes (walking and driving)?

Average 'first/last mile' distances are lowest in Seattle with 0.66 mi driving and 0.51 mi walking. They are substantially longer in Pinellas County with 0.80 mi driving and 0.61 mi walking and longest in Marin County with 0.89 mi driving and 0.71 mi walking. Overall, walking distances are *on average* shorter than driving distances, yet not for all trips. Figure 5 visualizes this difference for Seattle.

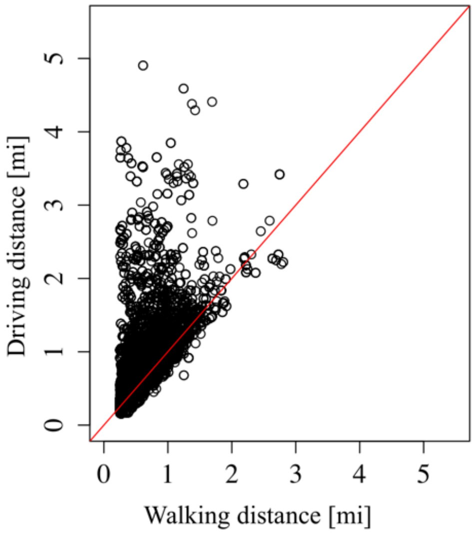

Figure 5. PT access/egress distances when walking and driving in Seattle.

We proceed with the results of our analyses on the impact of transfers and wait times on travel time savings using ridesourcing on the first/last mile.

5.1 Transfers and wait times

We find that first/last mile ridesourcing services yield substantial average gross travel time savings per trip in the three areas: from 12.12 min in Seattle to 18.23 min in Pinellas County and 20.50 min in Marin County. These differences can largely be explained with the large differences in first/last mile distances between the regions.

When adding transfer penalties and wait times, however, the outcome changes. A transfer penalty of 10 minutes (in-vehicle-time, equivalent to 5 minutes walking time) decreases the share of trips with perceived positive travel time savings from ~81% to 76% in Seattle. Adding 3, 5 and 10 min of wait time, decreases the share of trips with perceived positive travel time savings even further to ~59%, ~50% and ~25%, respectively. In other words: when we assume a transfer penalty of 5 min walking time equivalent for the first mile transfer and a wait time of 6:40 min for each ridesourcing trip, the share of trips that yields positive travel time savings decreases from ~81% without such assumptions to just ~25%. For Pinellas and Marin Counties, the impact is similar yet less pronounced due to longer first/last mile distances (see Table 2 for results for all three case studies).

Table 2. Travel time savings (walking time equivalent) after application of transfer penalties and wait times.

	Pinellas County	Marin County	Seattle
Mean first/last mile distance (>0.25 mi)			
- walking	0.61 mi	0.71 mi	0.51 mi
- driving	0.80 mi	0.89 mi	0.66 mi
Mean gross travel time savings per trip (0 min wait time, 0 min transfer penalty)	18.23 min	20.5 min	12.12 min
% of trips with travel time savings > 0 after application of			
- 0 min wait time, 0 min transfer penalty[1]	95.87%	96.15%	80.96%
- 0 min wait time, 10 min transfer penalty[1]	93.67%	94.63%	76.00%
- 3 min wait time, 10 min transfer penalty[1]	83.09%	86.60%	58.98%
- 5 min wait time, 10 min transfer penalty[1]	75.50%	80.64%	50.35%
- 10 min wait time, 10 min transfer penalty[1]	50.09%	60.04%	24.53%

[1] Transfer penalty in in-vehicle-time, subsequently converted into walking time.

These results confirm our conceptual argument: first/last mile services quickly lose their appeal in cities with short first/last mile distances/good PT accessibility (here: Seattle) and only remain attractive in regions with longer first/last mile distances (here: Marin County). This, however, raises the question whether the value of travel time savings exceed surcharges.

5.2 Costs

We find that *unsubsidized* costs for ridesourcing on the first/last mile exceed the value of travel time savings for most trips and income levels. For a first visual impression, see Figure 6. Here, we plot *VTTS - Lyft price* at four different household incomes for first/last mile rides in Seattle. Clearly, negative observations outweigh the positive ones, indicating that *unsubsidized* costs for ridesourcing on the first/last mile exceed VTTS for most trips and income levels.

Households with an average yearly income of USD 15,000 face lower VTTS than surcharges for all *unsubsidized* first/last mile rides below 1.43 mi. Households with an average yearly income of USD 90,000 face lower VTTS than surcharges for all *unsubsidized* first/last mile rides below 0.51 mi. Average values by distance are indicated for each household income level by the lowest (solid) red line.

Different subsidy schemes increase this financial viability of first/last mile rides differently. A 20% discount is least effective (average values by distance are indicated by the middle dotted red line). Under such a subsidy scheme, households with an average yearly income of USD 15,000 (USD 90,000) face lower VTTS than surcharges for all first/last mile rides below 1.03 mi (0.40 mi). A 5 USD discount is most effective (average values by distance are indicated by the top dotted red line). For most trips and household incomes VTTS now exceed surcharges.

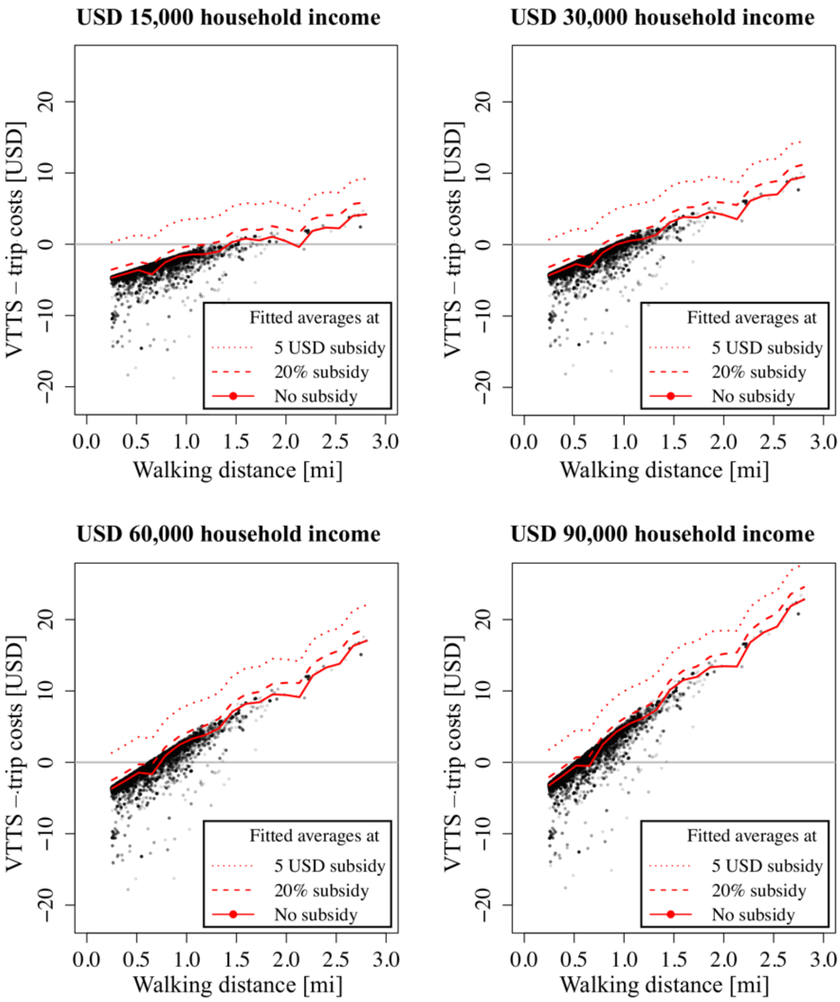

Figure 6. VTTS - Lyft price at four household incomes for first/last mile rides in Seattle with fitted averages (red lines) for different subsidy schemes.

Table 3 summarizes the effectiveness of different subsidy schemes for all three regions. Overall, ridesourcing costs on the first/last mile *without a subsidy* exceed VTTS for the majority of trips in all regions and for all household incomes. A 20% discount does not change much, particularly the shares for low-income households (< USD 30,000 yearly household income) remain low (i.e., below 17% of all trips for all regions). While a USD 5 subsidy per trip (as employed in the Pinellas County first/last mile pilot) is most effective in Seattle (even for low-income households, the share of trips where VTTS exceed subsidized ridesourcing costs now rises to 96-97%), it is much less effective in Pinellas and Marin Counties. Here, the 1.75 USD flat fee (as currently piloted in Los Angeles) is most effective. This can be explained by the distance of first/last mile rides. On average, it is much lower in Seattle, which results in lower overall ridesourcing costs and a higher impact of a 5 USD subsidy per trip.

Table 3. Share of trips where VTTS exceed ridesourcing costs/surcharges on the first/last mile for different household incomes at different subsidy schemes.

	Pinellas County	Marin County	Seattle
Share of trips where VTTS exceed ridesourcing costs on the first/last mile *without a subsidy* at VTTS corresponding to different annual household incomes			
USD 15,000	0.4%	0.9%	0.7%
USD 30,000	2.9%	5.8%	6.1%
USD 60,000	17.2%	24.8%	17.9%
USD 90,000	29.2%	36.7%	27.8%
Share of trips where VTTS exceed ridesourcing costs on the first/last mile *with a 20% discount* at VTTS corresponding to different annual household incomes			
USD 15,000	1.8%	2.8%	3.0%
USD 30,000	12.1%	16.1%	12.7%
USD 60,000	30.6%	38.8%	28.9%
USD 90,000	44.5%	55.2%	42.8%
Share of trips where VTTS exceed ridesourcing costs on the first/last mile *with a USD 5 subsidy* at VTTS corresponding to different annual household incomes			
USD 15,000	40.3%	46.5%	95.6%
USD 30,000	61.9%	69.0%	97.3%
USD 60,000	85.2%	86.2%	98.2%
USD 90,000	96.5%	95.5%	98.9%
Share of trips where VTTS exceed ridesourcing costs on the first/last mile *at a USD 1.75 flat fee* and VTTS corresponding to different annual household incomes			
USD 15,000	66.4%	74.9%	50.0%
USD 30,000	90.0%	92.8%	80.9%
USD 60,000	99.8%	99.8%	98.5%
USD 90,000	99.9%	100.0%	99.2%

In summary, choosing the right subsidy scheme is crucial to make first/last mile ridesourcing trips viable. For regions with short first/last miles, a USD 5 subsidy per trips appears as suitable, while for regions with longer first/last miles, a flat fee has a higher impact. It should be noted that the impact is most pronounced for higher income households. For those with lower annual household incomes (i.e., lower than USD 25,000 as 46% of bus-using households (Clark, 2017)), surcharges often still exceed VTTS despite subsidies. Last but not least, the impact of transfer penalties, wait times and surcharges are cumulative. In our cost calculations, we considered gross travel time savings (i.e., without wait times or a transfer penalty) only. In reality, however, transfer penalties and wait times reduce perceived travel times, which then further reduce VTTS. Our cost estimates can therefore be regarded as a lower bound.

6. Conclusions

In the outset of this paper we observed that many transit agencies in the US (and increasingly in Germany, too) partner with ridesourcing companies to offer subsidized first/last mile services. Ridership, however, has been lower than expected and some pilots had to be discontinued. So-far, explanations for low ridership have been related to specific implementation issues (e.g., sparse marketing, short pilot duration, small pilot area, high operational costs).

In this paper, we explored two conceptual explanations. First, using a ridesourcing vehicle for the first/last mile adds an additional transfer and wait times to a trip. The associated disutility reduces perceived travel time savings when compared to the alternative (walking). Assuming equal walking/driving distances (i.e., sidewalks alongside the road) and common average walking/driving speed estimates (3 mph and 20 mph, respectively), a transfer penalty of 5 min (walk time equivalent) for first mile transfers and a wait time of 3:20 min (walk time equivalent) exceed travel time savings through a first/last mile ridesourcing service for all distances lower than 0.45 miles.

Second, using ridesourcing for the first/last mile entails additional costs to be borne by the user. Following the common assumption of increasing values of travel time savings with increasing household income, we find that for equal walking/driving distances and Seattle Lyft fares without surge pricing, unsubsidized costs exceed the value of travel time savings for all distances below ~1 mile for households with USD 30,000 annual income. For households with less income, this distance further increases due to decreasing values of travel time savings.

As first/last mile distances are likely to differ by mode, which we assumed to be equal for our conceptual argument above, we proceeded with an empirical evaluation of commuting trips for three case studies. For Seattle (WA), we found that when assuming a transfer penalty of 5 min (walk time equivalent) for the first mile transfer and a wait time of 3:20 min for each ridesourcing trip, the share of trips that yields positive travel time savings decreases from ~81% without such assumptions to just ~25%. For suburban Pinellas (FL) and Marin (CA) counties with longer first/last miles, the impact is less profound, however nonetheless substantial.

Ridesourcing costs on the first/last mile *without a subsidy* exceed VTTS for the majority of trips in all regions and for household incomes. We proceeded testing three common subsidy schemes. A 20% discount has no substantial impact. A USD 1.75 flat fee increases the economic viability substantially, particularly in regions with long first/last mile distances (i.e., Pinellas and Marin Counties), while a USD 5 discount increases the economic viability particularly in regions with short first/last mile distances (i.e., Seattle). Higher income households benefit more from first/last mile ridesourcing services. For those with lower annual household incomes (i.e., lower than USD 25,000 as 46% of bus-using households (Clark, 2017)), surcharges often still exceed VTTS despite subsidies. These results are consistent with Alemi et al. (2019), who find that individuals with higher willingness to pay for travel time savings use ridesourcing more often. They also correspond with Yap et al. (2016), who conclude from their SP experiments that autonomous vehicles for the first/last mile are preferred over alternative modes only by first class train riders. Public subsidy schemes, though, usually endeavor to serve all members of the public equally. Instead of flat fees, fixed value or percentage-based discounts, full fare integration (as currently piloted in Seattle) offering first/last mile rides for free *if previously or subsequently PT is used* presents the most equitable solution, especially where low demand bus routes are discontinued simultaneously. Integration of first/last mile payment with transit smart card systems (as currently piloted in Seattle as well) further allows to monitor and prevent misuse of subsidies by using ridesourcing at a PT fare for a direct connection without subsequently/previously using PT[6].

Given our two conceptual explanations, it is not surprising that many first/last mile ridesourcing partnerships have experienced low ridership. Our findings also help explain why a significant and substantive positive relationship between ridesourcing and PT ridership (i.e., higher ridesourcing ridership leading to higher transit ridership) has not yet been found. Current PT users might find that surcharges exceed the value of travel time savings or the disutility of the additional transfer exceeds perceived travel time savings (especially for short distances). Potential new PT users face a different set of barriers. Despite improved first/last mile connections for some trips, the private car continues to be more comfortable, less costly (if only out-of-pocket expenses are considered) and faster (for our three case studies, the average car ride is between 4.1x and 5.4x faster than PT). Investments only in first/last mile improvements to increase PT usage, particularly in urban areas, are therefore likely to miss their purpose.

Our work can be complemented and expanded in several ways. First, booking data for first/last mile services (ideally, coupled with PT smart card data to obtain information not only about the

[6] Booking data from one subsidized first/last mile service suggests that several rides were conducted as direct trips (i.e., without previous/subsequent PT rides), essentially using the subsidies to pay for the (entire) cost of short taxi rides.

first/last mile, but about the entire trip) could shed light into real use cases. Combined with data on walking + transit trip combinations, this data could be used to verify our hypothesis on the impact of transfer penalties, wait times and surcharges empirically. Second, we have not allowed riders to bypass a transit-to-transit transfer in their intermodal routes using the first/last mile service (i.e., 'ridesourcing + rail' instead of 'ridesourcing + bus + rail'). This could have led to an underestimation of the potential benefit of a ridesourcing feeder service. Future studies could employ agent-based models that include trip-level optimization heuristics to test this hypothesis. Third, our literature review revealed a clear need to obtain empirical estimates for the 'pure transfer penalty' (i.e., without wait and walk time) between on-demand ridesourcing services and scheduled transit services (ideally, separating first and last mile services to account for their differences). Fourth, we only considered ridesourcing as an alternative access/egress mode. Future work could include the bike and discuss, where investments in bike infrastructure might yield higher benefits (also in terms of health and safety) than first/last mile ridesourcing subsidies. Fifth, we did not consider ride pooling as current rates are low even where pooled rides are requested (Henao and Marshall, 2018; Li et al., 2019). As adoption rates increase, ride pooling might become more frequent, which might impact travel times and costs of (usually pooled) first/last mile ridesourcing services. Thus, extending our analyses to include ridepooling would be beneficial especially in cities where already common.

Finally, our analyses are not limited to current variants of ridesourcing. Several scholars have proposed autonomous taxis as future first/last mile solutions (e.g., Chong et al., 2011; Liang et al., 2016; Yap et al., 2016). Our results challenge this view as transfer penalties and wait times persist for any vehicle-based first/last mile services. Studies aiming to quantify the potential of autonomous taxis on the first/last mile (e.g., Scheltes and de Almeida Correia, 2017; Shen et al., 2018; Wen et al., 2018) might come to a different conclusion once considering moderate wait times and penalties for first mile transfers between the feeder and transit.

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