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On-demand ride hailing as publicly subsidized mobility: An empirical case study of *Innisfil Transit*

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ABSTRACT

This empirical case study examines *Innisfil Transit*, a partnership between Uber and the low-density, rural Town of Innisfil, Ontario. Innisfil Transit subsidizes on-demand ride-hailing trips starting or ending within the town limits as an alternative to fixed-route transit. The Innisfil Transit program underwent multiple policy changes, providing an opportunity to learn about the links between program design (e.g. presence of fixed fare destinations, ride subsidies, and monthly limits) and ridership. This study has access to unique ridership data provided by Uber for the Town of Innisfil between 2016 and early 2020. Using descriptive statistics, cross sectional models, and panel models, this study explores the predictors of ridership and growth between 2016 and 2020 as a function of spatial, socioeconomic, and policy-related variables. Results indicate that program design (most critically – the presence of fixed fare destinations) has strong impacts both on the distribution of ridership and its growth over time, but that the allocative impact on total ridership across the town is unclear. Findings from this paper indicate that transit managers and council members of small communities considering subsidized on-demand ride hailing as an alternative to fixed-route transit should think carefully about what the program goals are and who is likely to benefit most.

1. Introduction

The adoption of ride-hailing services provided by Transportation Network Companies (TNCs) since their emergence around 2009 is providing new challenges and opportunities for transportation policy (Thomas et al., 2021). Understanding ride-hailing use and the adoption of new mobility tools (e.g. e-bikes, e-scooters, car sharing, etc.) is crucial for estimating and shaping future travel patterns and consequent impacts on cities (Clewlow and Mishra, 2017; Murphy and Feigon, 2016). Since 2015, over 40 partnerships between public transit agencies and private TNCs have emerged to provide ride hailing services as a form of public transit by subsidizing certain ride hailing trips (Curtis et al., 2019).

This study provides insight on the use of subsidized on-demand ride hailing as a tool to provide a base level of mobility and is unique for three core reasons. First, subsidizing on-demand ride hailing (e.g. Uber or Lyft) as an alternative to fixed-route transit is a novel approach to delivering public transit services. Second, understanding how subsidized on-demand ride hailing is used in a small-town context can provide guidance to other places. Third, this study uses unique ridership data provided by Uber to explore the potential for a ride-hailing-as-transit program to generate ridership by focusing on the case study of "Innisfil Transit."

Innisfil Transit was proposed and ultimately adopted as an alternative to a fixed-fare bus route due to the potential to serve more dispersed origin–destination pairs in a rural context (Town of Innisfil, 2017). Innisfil Transit provides publicly subsidized Uber services for residents of the town to and from any location within the municipality. The program was launched in May 2017 and is provided through the UberPool platform. Uber had first come to Innisfil approximately-one year earlier and was still gaining market share prior to the launch of Innisfil Transit. Since its implementation, the Innisfil Transit program underwent multiple policy changes, and saw a growth in monthly ridership from 519 (average of 17 per day) trips when the program launched in May 2017 to a peak of 15,800 trips (average of 512 per day) in March 2019. This study focuses exclusively on the period preceding March 2020 based on data availability.

Knowledge of ride-hailing use is based on both survey data of individual users and a limited number of ecological studies based on spatial exploration of ridership data provided by TNCs (Tirachini, 2020). While

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survey data can be collected more easily, survey participants' responses with respect to low-frequency and/or newer services need to be independently validated using more comprehensive ridership data available from service providers. However, because ridership data is typically owned by private TNCs, the availability of spatial data for analysis is limited. This leaves a large gap with respect to researchers' capacities to learn about system usage and to explore the conditions under which this technology advances broader public interests. Even transit agencies who partner with TNCs to provide subsidized ride-hailing programs have generally only received summary data from TNCs, making formal evaluation of pilot programs difficult (Curtis et al., 2019; Lucken et al., 2019; Schwieterman et al., 2018).

This study helps fill this gap in understanding both the adoption and policy impacts with respect to managing / supporting unsubsidized and subsidized ride hailing. In this study, the availability of Innisfil Transit and Uber ridership data represents a unique opportunity to better understand how ride-hailing is adopted in North American rural, small towns and to explore how the configuration of a publicly subsidized ride-hailing program can shape use. As such, this study focuses on two core research questions. First, how does a subsidized ride-hailing program (Innisfil Transit) impact ride-hailing use? And, how does the use of subsidized ride-hailing differ from unsubsidized ride hailing? Second, what are the spatial and temporal patterns of subsidized and unsubsidized ride-hailing use in a rural small town? Findings are interpreted towards informing policy makers who are considering implementing subsidized ride hailing in rural communities and under similar circumstances.

Towards answering these questions, first the existing literature on ride hailing users and ride hailing as public transit is covered. Next, the Innisfil Transit case study is presented, unique data provided by Uber is discussed, and inferential modeling approaches (both cross-sectional and panel models) are introduced. Results are presented based on the cross-sectional and panel models. Findings are discussed and conclusions are ultimately drawn for public transit operators interested in similar partnerships.

2. Literature review

While research on publicly subsidized ride hailing has been more emergent, significant bodies of work have already more broadly explored the users and implications of ride hailing in general. Towards understanding how program design can impact the use of subsidized ride hailing in rural communities, this study highlights lessons from existing literature on two key topics: who uses ride-hailing? and what are potential opportunities of for on-demand ride hailing to support public transit?

2.1. Ride hailing users

Adoption of app-based ride-hailing services provided by TNCs, such as Uber and Lyft, has increased rapidly since 2009 (Tirachini, 2020). Ride-hailing is displacing taxi rides in many jurisdictions (Clewlow and Mishra, 2017; Correa et al., 2017; Rodier, 2018). Understanding the rapid spread and disruptive nature of TNC ride-hailing services has challenged researchers and practitioners to disentangle the hype from the longer-term opportunities and liabilities of this new bundle of services (Thomas et al., 2021; Tirachini, 2020).

Multiple studies have explored ride hailing use. First, survey-based behavioral studies have found that younger, wealthier, and more highly educated people are more likely to use ride hailing (Grahn et al., 2020; Sikder, 2019; Young and Farber, 2019). Ecological studies employing zonal ridership data have explored the geographic and sociodemographic characteristics of ride-hailing users, leading to similar results as with individual survey data. For example, areas with higher income, younger demographic groups, and a more highly educated population are more likely to have high rates of ride hailing (Brown, 2019; Ghaffar et al., 2020; Lavieri et al., 2018; Marquet, 2020). But because georeferenced ridership data is typically privately owned by TNCs, ecological studies in North America have been more limited, and include Chicago, Austin, New York City, Los Angeles, Nashville, Seattle, and Washington DC, where researchers have gained access to private ride hailing trip data (Thomas et al., 2021; Tirachini, 2020).

Spatially, ride-hailing trips have predominately clustered near urban centers and in neighborhoods with higher population and job densities (Alemi et al., 2018; Thomas et al., 2021; Tirachini, 2020). However, ecological studies also indicate significant uptake of ride hailing in more suburban areas as well (Calderon and Miller, 2019). For example, Atkinson-Palombo et al. (Atkinson-Palombo et al., 2019), found that 56 % of ride-hailing total trips originated in New York's outer boroughs (Atkinson-Palombo et al., 2019). Brown (Brown, 2019) similarly found that while Lyft rides in Los Angeles were most frequently taken in denser urban areas, ride-hailing was also prominent in suburban and rural areas. Lessons on the geography of ride hailing and associated trip purposes are still emerging and have yielded different findings. While Feigon and Murphy (Feigon and Murphy, 2018) found that denser areas had more evidence of commuting via ride hailing, a City of Toronto (City of Toronto, 2019) study found that suburban areas (rather than more urbanized areas) had more evidence of commuting via ride hailing.

Studies show that despite ride-hailing being used predominantly by wealthier residents, it may be used as a tool to meet mobility needs among equity-seeking groups. In the Canadian context of the Greater Toronto Area, Shi and Sweet (Shi and Sweet, 2020) find that "low-mobility" travelers, who are less likely to be employed, have fewer cars per household, have a high reliance on public transit, and are the second largest market segment of ride hailing users, behind multimodalists. Similarly, Atkinson-Palombo et al., find that ride hailing use in the outer boroughs of New York – particularly among low-income, minority, and low car ownership populations, had a 40-fold increase in ride hailing from 2014 to 2017 (Atkinson-Palombo et al., 2019). Similarly, Lavieri et al. noted that while zones with higher incomes were associated with increased weekday ride hailing trips, but they were also negatively associated with weekend trips (Lavieri et al., 2018). In her study of ride hailing trips in Los Angeles, Brown (Brown, 2019) found that while a larger portion of ride hailing users lived in high-income areas, users who lived in low-income areas made more trips.

2.2. Ride hailing as public transit

Given the rapid proliferation and disruptive nature of ride-hailing services, the presence of TNCs can have wide-ranging impacts on public transit use – as illustrated by the mixed empirical findings on these impacts. Ride hailing can either complement (Hall et al., 2018; Murphy and Feigon, 2016; Sikder, 2019) or substitute for public transit (Gehrke et al., 2019; Graehler et al., 2019; Henao and Marshall, 2019; Young et al., 2020), depending on contextual and program design factors. Other studies have found nuanced or mixed results, showing that ride hailing can complement or compete with transit depending on context (Diab et al., 2020; Li et al., 2021; Malalgoda and Lim, 2019). The integration of ride-hailing into a public transit system could ensure that they work in tandem instead of in opposition. Given the complex results on the effects of ride hailing regarding public transportation, partnerships with TNC to provided public transportation will have significant impacts on urban policy (Jin et al., 2018).

Transit agencies have entered partnerships with TNCs to provide on-demand services since around 2015, highlighting potential benefits of these partnerships (Curtis et al., 2019; Feigon and Murphy, 2018; Thomas et al., 2021). Subsidized ride hailing may increase equity, combat transit poverty in low-density areas, provided first-mile-last-mile connections, and provide mobility options to the elderly or people with lower household incomes and lower access to private vehicles (Allen and Farber, 2019; Shi and Sweet, 2020). TNCs likewise offer a potential for transit agencies to optimize resources and save costs –

particularly to offer services in low-density areas which are harder to serve with fixed-routes (Sather, 2018).

There are potential risks to partnering with TNCs to provide transit services. Day-to-day operations of these services fall to the TNCs, which can be challenging for public agencies to ensure high quality of service (Blodgett et al., 2017). There are also barriers to residents without access to smartphones or credit cards, and there can be difficulty in ensuring TNC vehicles are accessible to riders with disabilities (Cochran & Chatman, 2021; Pike and Kazemian, 2019; Thomas et al., 2021). There are also potential longer-term risks of outsourcing a quasi-public good to a private company (Blodgett et al., 2017). Furthermore, it is necessary for equity-based performance measures to be included into assessments of any on-demand transit partnerships to ensure that increased equity is achieved (Palm et al., 2020).

Since 2018, three comprehensive surveys of TNC partnerships in North America have been completed. Schwieterman et al. (Schwieterman et al., 2018) identified 30 partnerships between transit agencies and TNCs, including the Town of Innisfil. Curtis et al. (Curtis et al., 2019) compiled a comprehensive list of all known American transit agency partnerships with TNCs and identified 44 partnerships in 20 American State. Lucken et al. (Lucken et al., 2019) conducted another review which identified 62 partnerships between mobility companies and transit agencies in the United States, including micro-transit services like on-demand shuttles.

A common theme from the reviews of TNC partnerships is that data sharing and program evaluation would be beneficial (Lucken et al., 2019; Thomas et al., 2021). Only a quarter of the agencies interviewed by Curtis et al. (Curtis et al., 2019) received data from TNCs regarding origin and destinations of trips, and only half received summary information on the number of users or average trip length. Schwieterman et al. (Schwieterman et al., 2018) also noted the challenges that transit agencies have in acquiring data from TNCs, and highlighted that Innisfil Transit is one of the few where the transit agency has access to ridership data (Town of Innisfil, 2018; Town of Innisfil, 2019; Town of Innisfil, 2020). While some of the other partnerships have been able to produce evaluations of their programs (Centennial Innovation Team and Peers, 2017; United States Federal Transit Administration, 2020), many were not, and there has been little evidence based on spatial analyses of ridership data.

This analysis of ridership data of subsidized and non-subsidized ride-hailing trips in the rural town of Innisfil provides a unique opportunity to add to the existing literature. As noted, many of the partnerships with TNCs deliver subsidized ride hailing to specifical populations, such as users of regional rail or paratransit (Schwieterman et al., 2018). Innisfil Transit, however, is available to the entire population of the town. Innisfil Transit is also unique in that it was implemented instead of a fixed-route bus (Town of Innisfil, 2017). This study aims to fill the gap regarding ecological studies of spatial ride hailing data in rural areas, and to provide contributions to the literature by conducting an analysis on a new set of spatio-temporal ride hailing data which includes both regular ride hailing and subsidized ride hailing in the small Town of Innisfil.

3. Research design

This case study of the Town of Innisfil provides a unique opportunity to fill the dearth of evaluations of TNC-public sector collaborations to deliver mobility. The Innisfil Transit program (the combination of fixed fares, rebates, regulations, and their geography) was implemented in May 2017, one year after Uber started providing on-demand ride-hailing services. The Innisfil Transit program represents a subsidized on-demand ride hailing service which is provided by Uber in addition to Uber's unsubsidized on-demand ride hailing service. Descriptive statistics show ridership growth through February 2020. Inferential models are estimated to explore ride-hailing use and change over time in response to the implementation of Innisfil Transit and the policy changes. These models will explore (1) the impact of a subsidized-ride hailing program on overall ride-hailing use and uptake, and (2) the spatial and temporal ridership patterns of ride-hailing use and uptake in a rural context.

3.1. Case study

This study focuses on the case study of a subsidized on-demand ride hailing program ("Innisfil Transit") in the Town of Innisfil, Ontario, Canada, which has a population of approximately 37,000 people (see Fig. 1). Innisfil is a small (but growing) town in a rural setting located between two cities: it is directly south of the City of Barrie (population of approximately 140,000) and is approximately 100 km north of the City of Toronto (population of approximately 2.8 million). The Innisfil Transit program subsidizes on-demand ride-hailing for Innisfil residents and was implemented as an alternative to fixed-route bus services (Town of Innisfil, 2017). The Town of Innisfil does not have a local fixed-route transit operator, but is directly served by GO Transit, an inter-regional bus service linking Barrie with Toronto, and indirectly served by a GO Transit rail station in Barrie which connects with Toronto.

Uber began offering on-demand ride hailing services in the Town of Innisfil in May 2016. By May 2017, the town launched the "Innisfil Transit" program to provide subsidized on-demand ride-hail trips through the UberPool platform (Town of Innisfil, 2017). Eligibility was determined by the billing address used in the Uber App. The on-demand service was directly provided by Uber through its app. Subsidies are structured so riders can go to specific destinations, such as the Town Hall, by paying a fixed fare initially ranging from $3 to $5 (Town of Innisfil, 2017). These specified destinations are referred to in this study as "fixed fare destinations." Trips originating or destined for other locations in the town were discounted by a fixed amount (initially $5) relative to Uber's unsubsidized price (Town of Innisfil, 2017). There are no other TNCs operating in the Town of Innisfil market. During the study period, this means that two services were available (and both are accessed virtually identically through the Uber app): subsidized ride hailing (Innisfil Transit) and unsubsidized ride hailing (use of Uber without the fixed-fare and rebate subsidies available through the Innisfil Transit program).

Innisfil Transit underwent multiple policy changes over time:

- <u>May 2017</u> – Innisfil Transit services begin by providing $5 rebates to all trips starting or ending in Innisfil and providing fixed-fare services to select fixed-fare destinations.
- <u>March 2018</u> - The town added two additional fixed fare destinations (Town of Innisfil, 2018) due to the expected value of this decision conveyed through the democratic process.
- <u>September 2018</u> - Innisfil stopped subsidizing trips originating or ending outside of the Innisfil's boundaries, except for those going to and from the Barrie GO Station (Town of Innisfil, 2019).
- <u>April 2019</u> - Innisfil capped individuals' rides to 30 trips per month and increased fixed-fare destination costs by one dollar each (Town of Innisfil, 2019) due to escalating program costs.
- <u>October 2019</u> - Innisfil launched a Fair Transit Program, where eligible low-income households could apply to receive 50 % of all rides, be exempt from the 30-trip limit, and receive two free trips per month to the Innisfil Food Bank (Town of Innisfil, 2020). Sixteen residents had been approved for this program as of April 14, 2021 (Town of Innisfil, 2021).

3.2. Ride hailing data

This study explores how Innisfil Transit program design (the combination of fixed fares, rebates, regulations, and their geography) affects use and how on-demand ride hailing is adopted. Data are provided by Uber, Inc. through the Town of Innisfil. Data include both non-subsidized Uber rides and subsidized Innisfil Transit rides, occurring

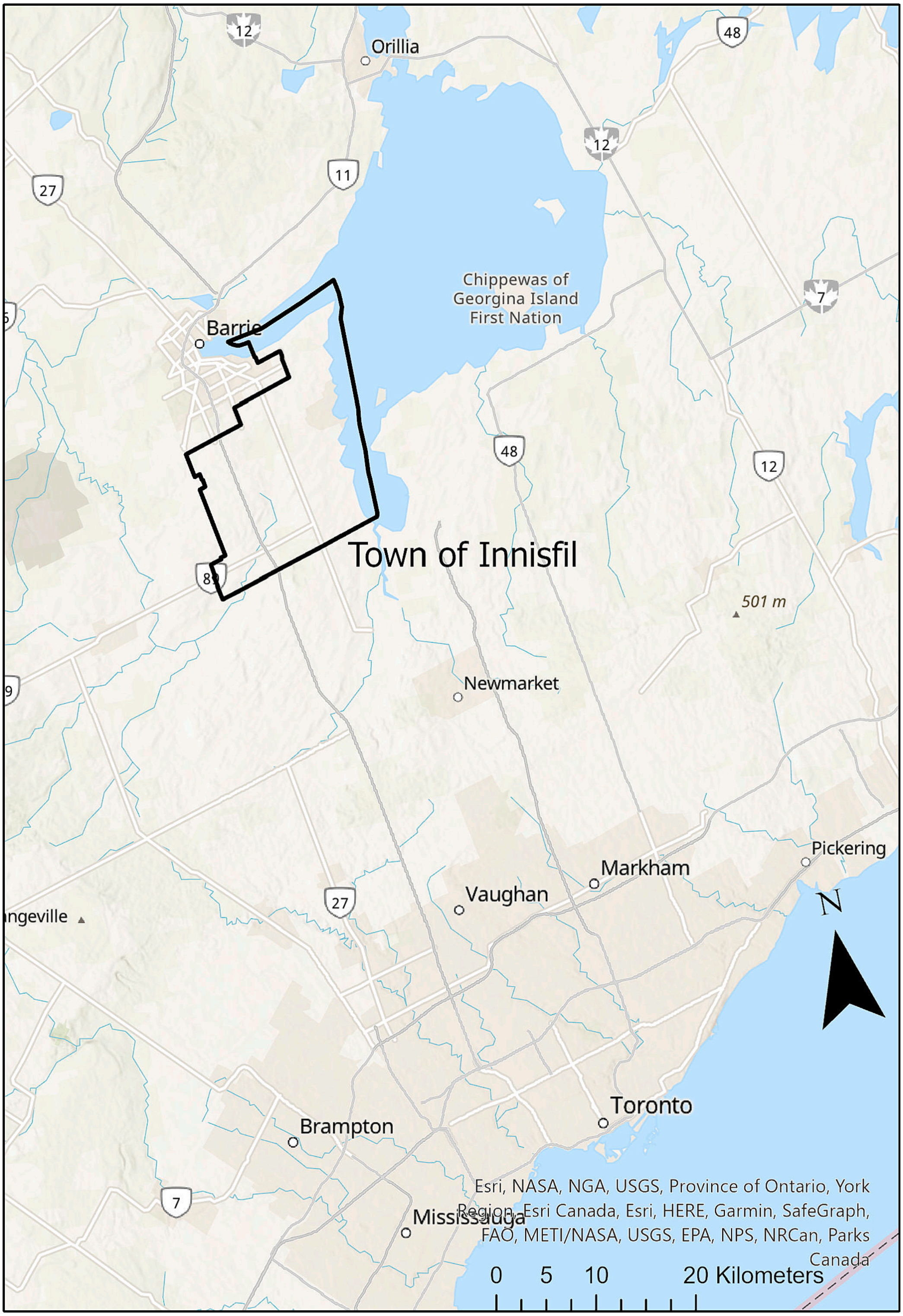

Fig. 1. Map of Town of Innisfil.

in Innisfil from May 2016 to February 2020 (i.e. over 46 months). Data for Innisfil Transit are available from the start of the program in mid-May 2017 and extend to February 2020. Spatial data is provided at the scale of 'Dissemination Areas' (DAs), which are the smallest geographical areas for which census data is disseminated by Statistics Canada (Government of Canada, 2016).

Innisfil is comprised of 59 DAs, and ridership data is available for 57 of them (the two remaining ones were geographically small and did not have any trips to or from them). DAs range in size, with the population of the Innisfil DAs ranging from approximately 270 to 5,120 individuals (with a mean of approximately 490), and their areas ranging from 0.7 km^2 to 40 km^2 (with a mean of approximately 5 km^2). Fig. 2 displays the DA boundaries as well as the spatial distribution of total trips per kilometer in each DA by both Innisfil Transit and Uber riders over the entire study period (including the sum of trip origins and destinations. Trips must have either originated or ended within one of the Innisfil DAs to be

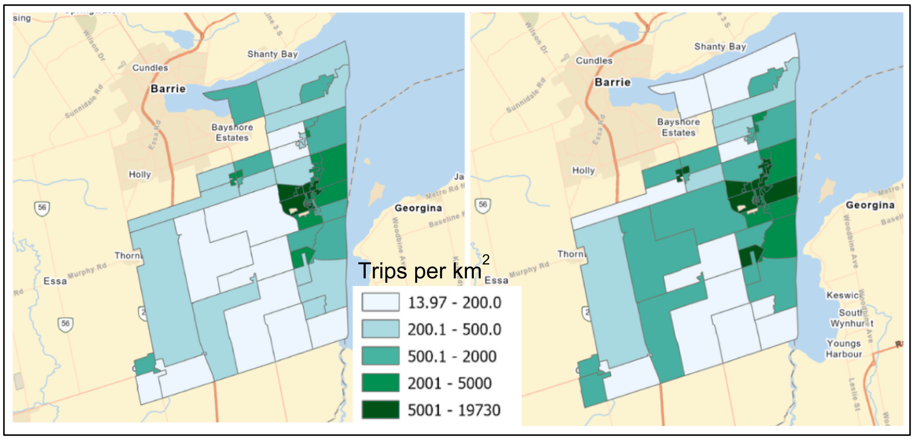

Fig. 2. Map of Innisfil DAs showing total incoming and outgoing Innisfil Transit trips per km2 (left) and Uber trips per km2 (right).

included in this study. As shown in Fig. 2, the number of trips per kilometer was most highly concentrated within the central area of Innisfil for both subsidized and non-subsidized trips.

Data provided by Uber are available by either the trip origin or by the trip destination and each of these are aggregated to individual DAs, individual months of the year, individual years ranging from 2016 to 2020, and based on distinctions between weekday or weekend, and different time periods (ranging from 6am-10am, 10am-3 pm, 3 pm-7 pm, 7 pm-10 pm, and 10 pm to 6am). When fewer than five trips occurred within a specific time and location/ DA (e.g. during a specific time period on a specific month during a specific day in a specific year), the information was masked by Uber as a condition of accessing the data to preserve privacy. This led 12 % of origin trips being masked and 11 % of destination trips being masked. This research paper looks only at the unmasked data and aggregates these to specific months for each DA.

There were approximately 344,000 Innisfil Transit trips (including the sum of pick-up and drop-offs) and 147,000 Uber trips completed during the study period within Innisfil. Three per cent of Innisfil Transit trips were shared with other users, five per cent of Uber trips were shared with other users, while the rest were single-passenger trips. Fig. 3 shows that total ridership experienced drastic growth from only 22 trips made in September 2016 to over 23,700 in January 2020, before decreasing to approximately 21,300 in the final month of the dataset. Once implemented in May 2017, there were more Innisfil Transit trips than Uber trips for the duration of the study period. Innisfil Transit ridership peaked at approximately 15,800 trips in March 2019, one month before a cap of 30 rides per user per month and increased fixed fare costs were implemented.

3.3. Modeling approach

Ridership data for both subsidized (Innisfil Transit) and unsubsidized (Uber) trips were compared controlling for a) various policy factors relating to the implementation and program design of Innisfil Transit, b) different built environment characteristics of zones (DAs), and c) socioeconomic characteristics of residents of those DAs. Ridership per zone is measured as the sum of trip origins and destinations, an approach similarly adopted in Brown (Brown, 2019) and Ghaffar et al. (Ghaffar et al., 2020). All variables are included in Table 1. Variables used to control for built environment characteristics and socio-economic factors were identified and tested based on the review of the existing literature and the specific context of the rural location of the Town of Innisfil. Due to scale effects, whereby more populous zones are anticipated to have more rides simply because more people live there, variables are transformed (e.g. to population density or population shares) to better preserve independence and normality (de Dios Ortuzar and Willumsen, 2011).

3.3.1. Program and policy changes

This study examines the impacts of the implementation and program design of a subsidized ride hailing service. Linear regression models are used to estimate the impacts of changes in Innisfil Transit policies and

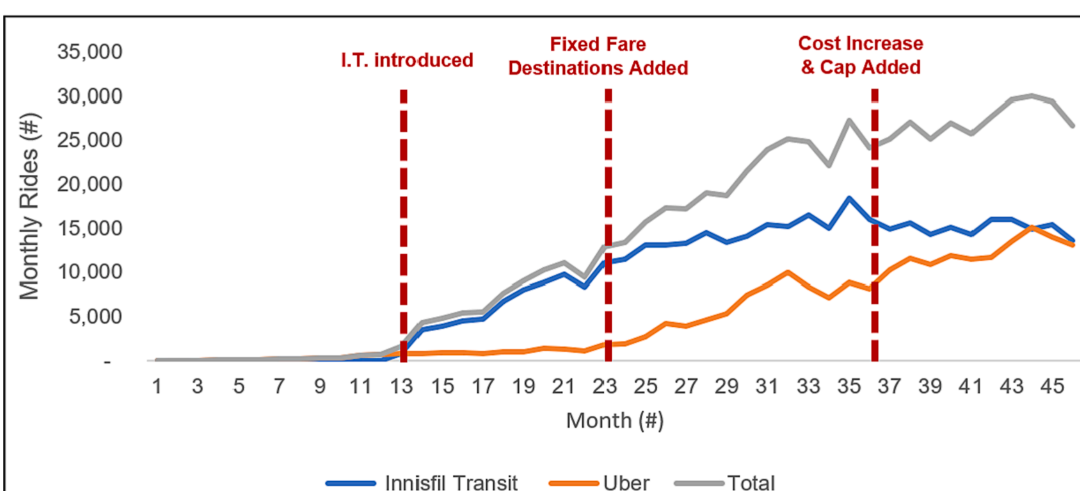

Fig. 3. Growth of ride-hailing trips (sum of pick-up and drop-offs) within Innisfil over the study period. *Note: I.T. refers to Innisfil Transit.*

Table 1
Summary Statistics of Variables per Dissemination Area.

Variable	*Max.*	*Min.*	*Mean*	*Median*	*St. Dev.*
Cross Sectional Dependent Variables					
Innisfil Transit Trips *	105,054	23	8,262	1,545	16,018
Uber Trips *	19,729	14	2,966	792	4,417
Total Trips *	122,258	43	11,228	2,166	19,946
Panel Dependent Variables					
I.T. Trips (Δ) *	9,601	0	155	1	804
Uber Trips (Δ) *	14,901	0	194	1	873
Total Trips (Δ) *	14,901	0	140	1	774
Policy Explanatory Variables					
Fixed Fare (yes = 1) **	1	0	0.16	0	0.36
Land Use Explanatory Variables					
Population Density per square km. ***	7,957	10	962	517	1,279
Road Density (link-kilometers per square kilometers) ***	3,337	1	339	50	615
EPOI Density (points per square kilometer) ***	101	0	14	4	22
Population ***	5,120	273	617	494	656
Area (square kilometers) ***	39.63	0.07	4.6	1.99	7.57
Socioeconomic Variables Explanatory Variables					
Male ***	57 %	40 %	50 %	51 %	3 %
Unemployed ***	13 %	0 %	5 %	4 %	3 %
Renters (1 = yes) ***	38 %	0 %	12 %	11 %	9 %
1-parent household (1 = yes) ***	31 %	7 %	14 %	13 %	5 %
Visible Minority (%) ***	28 %	0 %	5 %	3 %	6 %
Low Income (< $44 k/yr) ***	57 %	10 %	21 %	19 %	9 %
Middle Income ***	71 %	36 %	52 %	52 %	7 %
High Income (<$125 k/yr) ***	52 %	4 %	27 %	26 %	11 %
Average Annual Household Income ***	$363,000	$47,000	$104,000	$99,000	$41,000
Education – Bachelor -plus ***	32 %	2 %	12 %	11 %	6 %
Families with children ***	81 %	13 %	59 %	58 %	14 %
Population under 15 ***	26 %	1 %	15 %	15 %	5 %
Population aged 15–34 ***	34 %	2 %	23 %	23 %	6 %
Population aged 35 to 64 ***	54 %	22 %	45 %	47 %	7 %
Population 65-plus ***	73 %	5 %	17 %	13 %	16 %
Household maintainers aged under 35 ***	30 %	0 %	11 %	11 %	7 %
Household maintainers aged 35–64 ***	89 %	14 %	66 %	69 %	16 %
Household maintainers aged 65-plus ***	84 %	0 %	24 %	20 %	18 %
1-person households ***	47 %	7 %	18 %	16 %	9 %
2-person households ***	55 %	18 %	35 %	35 %	7 %
3-plus person households ***	71 %	4 %	47 %	49 %	14 %

Notes: EPOI = Enhanced Points of Interest; "I.T." denotes Innisfil Transit.
Notes: EPOI = Enhanced Points of Interest;
Sources: * Uber; ** Innisfil staff reports; *** 2016 Statistics Canada via SimplyAnalytics;

program design on ridership using both cross-sectional linear regression models (which capture longer-term patterns) and panel regression models with time-based fixed effects (which capture short-term associations). The following key dates and program changes are included in the models as policy variables:

- May 1, 2017 – Innisfil Transit launched, known as "Phase 1" (Town of Innisfil, 2017)
- March 15, 2018 – Two additional fixed fare destinations are added, known as "Phase 2" (Town of Innisfil, 2018)
- April 1, 2019 – Innisfil caps the number of monthly subsidized rides for individual users at 30 trips per month and increases fixed fare costs, known as "Phase 3" (Town of Innisfil, 2019)

Several policy variables are included in both cross sectional and panel models, both of which are estimated using ordinary least squares regression. We included binary indicators capturing whether one or more fixed fare destinations is located within a specific DA zone at that time (see Fig. 4). We also included a binary indicator of whether Innisfil Transit had been implemented at a particular time (pre vs during) in the panel models. We also included a binary indicator unique to the time when Innisfil Transit was implemented in May 2017 to test for a one-time ridership change rather than a structural change. Finally, we included a binary indicator of whether the cap on rides and subsidy reduction has been implemented or not (Phase 3).

3.3.2. *Model controls*

Models controlled for built environment factors including, population density, road density, and the density of Enhanced Points of Interest (EPOI) as a proxy for mixed land use (DTMI Spatial, Inc., 2016). EPOIs include recreational and business sites including but not limited to healthcare facilities, shopping centers, postal offices, golf courses and

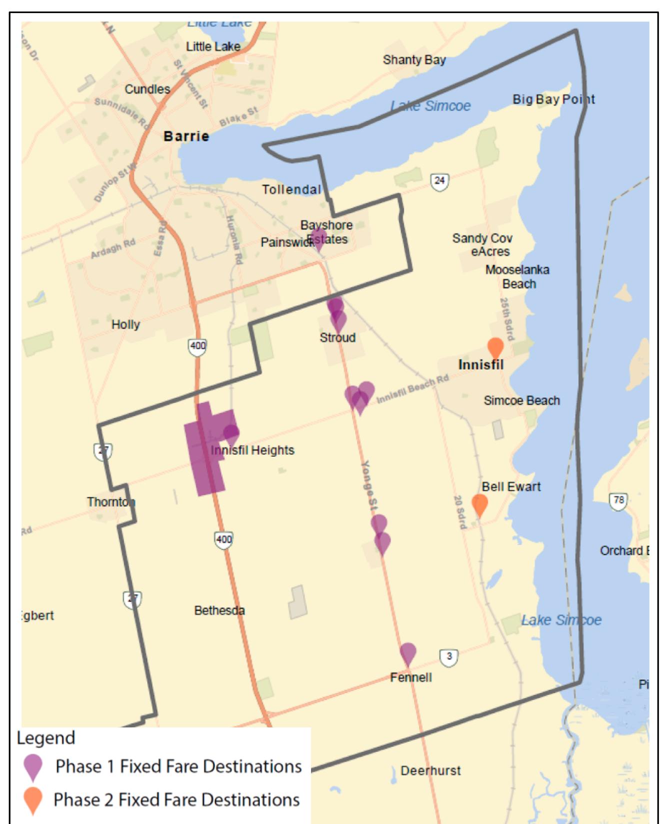

Fig. 4. Map of Fixed Fare Destination locations implemented in Phase 1 (May 2017) and additional locations added in Phase 2 (March 2018).

education facilities. The density of regional bus stops was initially tested but excluded from models due to poor fit.

Models controlled for multiple socioeconomic characteristics – each of which was derived from 2016 Statistics Canada data (preceding the Innisfil Transit program). Those controls include individual age and the age of household maintainers (who presumably have an outsized role in mobility decisions), household income, household size, number of children, housing tenure (renters vs owners), education, and the proportion of single parents in an area. A "household maintainer," is defined by Statistics Canada as the "person in the household identified as someone who pays the rent or the mortgage, or the taxes, or the electricity bill, and so on, for the dwelling (Government of Canada, 2016)". Both individual age and household maintainer age were categorized into three categories, similarly to the analyses by Ghaffar et al. (Ghaffar et al., 2020), Lavieri et al. (Lavieri et al., 2017), and Correa et al. (Correa et al., 2017): young adults (under 34), middle-aged adults (35 to 64), and older adults (over 65). Household income was also included using several income categories – similar to other studies (Atkinson-Palombo et al., 2019; Brown, 2019; Lavieri et al., 2017; Li et al., 2021; Yu and Peng, 2019). As in Ghaffar et al. (Ghaffar et al., 2020), we used the Pew Research Centre categories to distinguish between low (<$45,000), medium ($45,000-$125,000), and high (>$125,000) annual household incomes (Pew Research Center, 2016).

3.3.3. *Model estimation*

Using linear regression estimated using R, we estimated a) cross sectional models to explore predictors of ridership (which are arguably more indicative of longer-term associations) and b) panel models (which are indicative of more shorter-term links) to explore how on-demand ride hailing grew over time. Cross sectional models estimate the predictors of a) unsubsidized Uber ridership per zone, b) subsidized Innisfil Transit ridership per zone, or c) total (subsidized + unsubsidized) ride hailing ridership originating and terminating in each zone. We initially tested models using the dependent variable of total trips per square kilometer or per person due, but ultimately the metric of trips per square kilometer was used. However, cross-sectional results should be interpreted carefully due to the small sample size (N = 57) and therefore higher standard errors.

A panel regression model is used to estimate predictors of change in ride-hailing use per zone over time. The panel data examined the relationship between explanatory variables and the change in ridership per DA – measured as the ratio of trips in at a subsequent time period ($t + 1$) to an initial time period (t). While alternate lags were tested, a time lag of three months between time t and time $t + 1$ was preferred. In the panel models, observations were weighted to the proportions of trips made within a DA per month, as this approach gave more weight to higher-ridership zones to better reflect underlying ridership changes, rather than giving low-ridership zones the same weight as those with higher ridership. To control for general seasonality of ridership, time fixed effects were applied to the models.

We proceeded using an iterative stepwise approach to select the variables for each model and tested variables for multicollinearity. We started each model by including all variables and then systematically removed those that had estimated impacts which were statistically indistinguishable from zero. Certain variables were kept regardless of significance, including all the Innisfil Transit policy variables, as they are the focus of this study. Ridership data from the entire study period (May 2016 to February 2020) was used for the Uber and total trip models and this period included all days, regardless of weather, events, or external conditions. For the Innisfil Transit panel model, data only extending from May 2017 to February 2020 was included.

Table 1 displays summary statistics for the selected dependent and explanatory variables which were used in the iterative modeling approach, as well as data sources.

4. Results

This study presents ridership models to determine: (1) how did the Innisfil Transit subsidized-ride hailing program impact overall ride-hailing use and uptake, and (2) what are the spatial and temporal ridership patterns of ride-hailing use and uptake in a rural context? This study fundamentally uses a ridership model (which is cross-sectional) and a ridership change model (which is treated as a panel) which are commonly used and comprise the products of trip generation and mode share (de Dios Ortuzar and Willumsen, 2011). Models are validated through testing and by adopting a common approach which controls for expected predictors of Innisfil Transit ridership and ridership change based on expectations from utility theory.

4.1. *Cross sectional models*

The cross-sectional models (see Table 2**)** show that the presence of at least one fixed-fare destination has a positive impact on use in all three models. The coefficient is highest and the most statistically significant for the model focusing only on Innisfil Transit trips and shows that DAs with at least one fixed fare destination are expected to have 86 % more Innisfil Transit trips than DAs with none. This indicates that Innisfil Transit trips (which are subsidized) are more impacted by being subsidized as a fixed-fare destination than are unsubsidized Uber trips originated or terminated in DAs (which is intuitive). This supports the expectation that the Innisfil Transit subsidies are inducing ride hailing use by Innisfil residents. Results should be interpreted cautiously, as the cross-sectional sample size is quite low, leading practically significant results to not always be statistically significant.

Several control variables exhibit the expected signs. The strongest built environment predictor of all types of ride-hailing use is population density, which is found to be almost perfectly elastic. This (unsurprisingly) suggests that ride-hailing generally follows the geography of residential locations, which is also supported from previous study findings. A significant socioeconomic indicator is the proportion of adults aged 15 to 34 in each DA. This indicates that, as found in other

Table 2
Cross Sectional Model Results.

Ride Hailing Type:	Total Trips per Square Kilometer	Uber Trips per Square Kilometer	Innisfil Transit Trips per Square Kilometer
Variable	Coefficients[1]		
Policy			
Fixed Fare Binary	0.60(.)	0.38	0.86(*)
Land Use			
Log (Population Density)	1.12(***)	1.11(***)	1.19(***)
Log (Road Density)	−0.18(.)	−0.16	−0.21
Log (EPOI[2] Density)	0.20(*)	0.09	0.21(.)
Socioeconomic Demographics			
Log (Percent Age 15–34)	1.64(***)	1.56(***)	1.79(***)
Log (Percent Income < 44,0000)	0.86(.)	−0.02	0.97(.)
Log (Percent Income 45,000–125,000)	−0.76	−2.24(*)	−0.79
Log (Percent Education Bachelor +)	NA	0.53(.)	−0.64(.)
Log (Percent Unemployed)	−0.31(.)	−0.23	−0.38(.)
Intercept	4.06	−0.23	2.11
Adjusted R-Squared	0.81	0.83	0.79

Notes:
1. Statistical significance of 0.001 (***), 0.01(**), 0.05(*), and 0.1(.).
2. EPOI = Enhanced Points of Interest.
3. NA denotes that a variable was excluded from the model.

studies, areas with more young adults were much more likely to generate more ride hailing trips. The proportion of middle-income households is statistically significantly associated with lower ride hailing use in the Uber trip model only, while the proportion of low-income riders shows a weakly significant positive relationship to both total trips and Innisfil Transit trips. The proportion of individuals with an educational level of bachelor's degrees or higher is negatively associated with ridership for all three models but is only significant at the 0.10-level. This result differs from previous studies, which found that higher education was associated with increased ride hailing trip generation (Alemi et al., 2018; Grahn et al., 2020; Sikder, 2019; Young and Farber, 2019). It is possible that as a rural area, the job market and education dynamics may differ from those in urban cities.

4.2. Panel models

The panel models (see Table 3) use three-month lags to explore how on-demand ride hailing grew in the small town of Innisfil and to identify how Innisfil Transit program design and policies affected use. This approach is particularly unique, as previous spatial studies of ride hailing have only utilized cross sectional models to identify the predictors of ridership.

Table 3
Panel Model Results.

Ride Hailing Type:	Total (2016–2020)[1]	Uber (2016–2020)[1]	IT (2017–2020)[2]
Variables[3]	Coefficients[4]		
Policy			
Fixed Fare Binary	0.08(*)	0.20(.)	0.06
Capped Trips Binary	0.19(*)	0.04	−0.46(**)
Innisfil Transit One-Time Implementation Factor	−1.09	−1.06	NA
Innisfil Transit Binary	−0.04	−0.3	NA
Land Use			
Log (Population Density)	0.06(***)	0.18(***)	0.05(*)
Log (Road Density)	NA	−0.10(**)	−0.02
Log (EPOI[5] density)	0.02	0.07(*)	0.05(***)
Socioeconomic Demographics			
Log (Percent Age 15–34)	0.72(***)	0.34	0.27(*)
Log (Percent Age Household Maintainer < 34)	−0.04	−0.04	0.44(*)
Log (Percent Age Household Maintainer > 65)	0.04	0.11	0.13(*)
Log (Percent Income < 44,000)	0.25(*)	−0.37(.)	0.05
Log (Percent Income 45,000–125,000)	−0.46(*)	−0.93(*)	−0.11
Log (Percent Education Bachelor +)	−0.16(***)	−0.25(**)	−0.15(**)
Log (Percent Unemployed)	−0.11(***)	−0.18(**)	−0.7(*)
Log (Percent Visible Minority)	0.08(***)	0.08(*)	0.04(*)
Log (Percent Renters)	NA	0.08(.)	NA
Log (Percent Families with Children)	−1.49(***)	NA	NA
Log (Percent 1-Person Household)	0.10	0.23	NA
Log (Percent 3 + Person Household)	1.06(***)	0.79(*)	NA
Intercept	0.44	−1.35	0.44
Adjusted R-Squared	0.10	0.44	0.10

Notes:
1. Data for Total trips and Uber trips include the entire study period (May 2016 to February 2020).
2. Data for Innisfil Transit trips included from the implementation of Innisfil Transit onwards (May 2017 to February 2020).
3. Date fixed effects employed.
4. Statistical significance of 0.001 (***), 0.01(**), 0.05(*), and 0.1(.).
5. EPOI = Enhanced Points of Interest.
6. NA denotes that a variable was excluded from models.

The models of Uber (unsubsidized) and total trips (unsubsidized + subsidized) extend between May 2016 (one year before Innisfil Transit was launched) and February 2020, whereas the Innisfil Transit (subsidized trips) model was run for May 2017 to February 2020 (a period during which the program was in effect). Uber and total trip models were also estimated for the shorter timeframe (not presented here) when Innisfil Transit was in effect, but results are substantively consistent. These shorter timeframe models showed the same coefficients for all variables as the longer time frame models (summarized in Table 2). The panel models also highlight a statistically insignificant impact of capping trips on Uber (unsubsidized only) trips, while estimates suggest that capping trips decreased Innisfil Transit trips (subsidized) while aggregate trips increased (including both subsidized and unsubsidized trips). This provides weak evidence of substitution from subsidized to unsubsidized Uber trips upon implementing the 30-trip cap.

Regarding the implementation of Innisfil Transit, the one-time variable which looked specifically at the change in trips from April 2017 to June 2017 was statistically insignificant (but negative) for both Uber and Total trips, indicating that on-demand ride-hailing was largely unaffected in the immediate aftermath of Innisfil Transit being implemented. The Innisfil Transit binary variable (which tests whether the growth rate structurally changed after Innisfil Transit was implemented) shows a statistically insignificant link with total trips and with Uber trips.

Results show that the presence of at least one fixed fare destination in a DA had a complex relationship with ridership. While it had a significant impact on overall on-demand ride hailing (0.05-level), its effect was only significant at the 0.10-level in the model of Uber (unsubsidized) trips and it was highly insignificant in the model of Innisfil Transit (subsidized) trips. This finding is counterintuitive, implying that the chief advantage of fixed fare destinations was Uber and their users, rather than the Innisfil Transit program users themselves. Coefficient estimates suggest significant effects – leading one to expect an eight percent on-demand ride hailing (all) growth premium in zones with a fixed-fare destination and a 20 percent premium in Uber (unsubsidized) use.

Regarding the built environment, population density is associated with trip growth in all three models and is most strongly associated with growth in Innisfil Transit use. Like the cross-sectional models, this indicates that more urbanized areas continued to draw more riders over time.

In terms of socioeconomic variables, the proportion of young adults living in a DA is positively associated with higher ridership growth in all three models. This indicates that young adults increased their use over time for both subsidized and non-subsidized trips. The panel models also indicate that a higher share of young adult household maintainers is associated with lower ridership growth in both Uber and total trip models. Alternatively, young adult household maintainers were associated with increased Innisfil Transit ridership. This indicates that young people running a household may act differently than young adults without such responsibility and take more advantage of subsidized trips.

Middle income households are negatively associated with ridership in all three models. The proportion of low-income households is once again positively associated with the Innisfil Transit and Total trip models, but negatively associated with the Uber model. This further supports the possibility that Innisfil Transit is more likely to be used by low-income households, though the results are only significant for the total trip (0.05-level) and Uber (0.10-level) models, but not the Innisfil Transit model. This is somewhat different from the cross-sectional model, in which higher shares of low-income households was most strongly associated with Innisfil Transit ridership (as well as total ridership), but not with Uber ridership.

The three models indicate that both higher education levels and higher unemployment are associated with lower trip growth rates. It may be expected that these findings could be a function of Innisfil's rural character and the different labor market than in major urban areas in which many similar studies have been conducted to date. Like in cross-sectional models, a higher share of unemployed individuals is associated with lower ridership growth in all three models – implying lower travel demand among this population sub-group. The proportion of visible minorities is likewise associated with increased ridership in all three models. These results are consistent with the findings of Atkinson-Palombo et al. (Atkinson-Palombo et al., 2019) who found that ride-hailing was growing at a faster rate in the outer boroughs of New York, many of which have low-income, minority populations.

5. Discussion

Understanding how public actors can impact the private provision of on-demand ride hailing is crucial towards shaping new technologies for the public interest. Using public resources to subsidize on-demand ride hailing has become one possible means for municipalities to augment available mobility tools – particularly in lower density and small-town communities with a poor outlook for fixed-route transit services. This study helps fill this gap using the case study of Innisfil Transit, a subsidized on-demand ride hailing program in a rural, small-town context in Southern Ontario, Canada. This paper uses Uber trip data to explore the changes in and predictors of usage over time while estimating the impacts of policies and program design (notably the allocation of fixed-fare destinations, program implementation, ride limits, and fare subsidies) through the "Innisfil Transit" program.

Results indicate that policy decisions with respect to subsidizing fixed-fare destinations have complex impacts on on-demand ride hailing. The presence of a fixed-fare destination has the strongest and most robust impact on the distribution of ridership, indicating significant increases in overall on-demand ride hailing in zones with fixed-fare destinations (summing subsidized and unsubsidized trips). Between a 60 and 86 percent increase in ridership, respectively, for all on-demand ride hailing and for Innisfil Transit trips (which are subsidized) can be expected in zones with a fixed-fare destination (based on cross-sectional models). The effect on Uber ridership (which is unsubsidized) is positive (38 percent premium) but is statistically indistinguishable from zero. In contrast, the panel models indicate that on-demand ride hailing trips (including both subsidized and unsubsidized trips) grew eight percent faster in areas with a fixed fare destination, but the impacts on Innisfil Transit ridership were insignificant, while impacts on Uber ridership were marginally significant (0.10-level) despite their large magnitude (an expected 20 percent premium). Together these findings suggest that as much as fixed fare destinations appear to be a tool for deploying Innisfil Transit, the most robust impacts of the program were on increasing overall on-demand ride hailing (including both subsidized and unsubsidized trips).

Other ridership responses to policy actions were more complex. For example, the implementation of the 30-trip monthly trip cap was associated with a 46 percent reduction in subsidized ride-hailing trip generation but was associated with a 19 percent increase in overall on-demand ride hailing trips (subsidized + unsubsidized). As such, while the implementation of the 30-trip monthly trip cap clearly served to reduce subsidized trip taking (and hence public costs to Innisfil Transit), residents appear already to have developed habits of using on-demand ride hailing, leading to a (counter-intuitive) increase in total trips – ironically both reducing the public cost of Innisfil Transit and increasing the total on-demand ride hailing ridership (and implicitly the private revenues by Uber). This begs to question whether Innisfil Transit may have simply accelerated and normalized the adoption of ride hailing – leading to deeper and more rapid adoption by residents (and consequently more business opportunities for Uber).

In panel models, policy controls with respect to the one-time implementation of Innisfil Transit and potential structural impacts of Innisfil Transit on longer-term growth provide no strong evidence that Innisfil Transit affected overall on-demand ride hailing. In no model were either of the two variables statistically significant – suggesting that the allocative (rather than distributive) impacts of Innisfil Transit are indistinguishable from zero. Given that this study was not based on a control-treatment group research design due to data limits, this broader question of allocative vs distributive impacts should be further investigated. This study suggests that impacts are only distributive (impacting where rides are taken) rather than allocative (impacting the net growth of ride hailing ridership).

Other control variables are broadly comparable to other studies, which suggest that younger users and more urbanized areas have higher ride hailing usage (Alemi et al., 2018; Grahn et al., 2020; Sikder, 2019; Young and Farber, 2019). However, results between the models of Uber (unsubsidized) and Innisfil Transit (subsidized) suggest that these services may be used by different groups. Based on the panel models, Uber is less likely to be used by younger and older households, while income differences are not significant for Innisfil Transit. Likewise, Innisfil Transit appears to follow urbanization patterns more closely than Uber. These differences in who is served by subsidized or unsubsidized on-demand ride hailing should be further investigated in other contexts.

6. Conclusion

The results of this paper can be used by municipalities considering the implementation of subsidized ride hailing partnerships with TNCs. Findings suggest that opportunities for success are contextual and depend on program objectives (in addition to design). These findings are particularly important for low-density, rural municipalities with limited transit availability. Findings from this study provide no evidence that Innisfil Transit increased overall ridership of on-demand ride hailing in the town, but results do indicate that Innisfil Transit shaped where those rides occurred: more prominently in zones with fixed-fare destinations. This suggests that Innisfil Transit both reduced the cost of using on-demand ride-hailing and changed the geography of where on-demand ride hailing was used – tilting it more towards higher-density, fixed-fare destinations. This suggests that there are two primary benefactors of the program: 1) residents who benefitted from cheaper on-demand ride hailing costs (and may or may not have taken more trips as a result) and 2) Uber and their drivers, who likely benefitted from the lower cost of serving users who were more likely to travel to fixed fare destinations (which are more urban and centrally located) than serving even more dispersed and rural contexts (which are more costly to access). One could imagine local businesses which are well served by fixed fare destinations to likewise benefit from increased traffic from on-demand ride hailing users, but this is beyond the scope of this study.

Municipalities considering a similar approach to subsidize on-demand ride hailing through a partnership with a transportation network company, such as Uber, should carefully consider their desired outcomes and ensure clear goals. This study paints a complex picture, whereby fixed fare destinations appear to be the most important factor shaping the distribution of ridership. In the absence of a treatment–control research design, it is impossible to say whether on-demand ride hailing use would have been higher or not if Innisfil Transit had not been implemented. Results from this finding provide no evidence of Innisfil Transit affecting total ridership, but the increase in on-demand ride hailing which coincided with the start of Innisfil Transit (see Fig. 3) suggests that the program very well could have increased ridership in Innisfil beyond what it would have been. Other research needs to explore this question.

Transit managers should carefully consider who they hope will benefit from subsidized ride-hailing, and how to ensure that they do. Many small towns and rural contexts are not well suited for fixed-route bus routes, making subsidized on-demand ride hailing a potential alternative. The Town of Innisfil's need to institute a 30-trip monthly maximum per user illustrates the popularity of the program and (hence) the escalating public costs of continuing to subsidize ridership at such high levels. The possibility of induced demand for on-demand ride hailing raises many normative questions – notably about the role of the public sector in reducing transportation costs among existing users, the role of the public sector in inducing additional auto-based travel demand, and the potential to provide a base level of mobility in communities which are not designed for fixed-route public transit. These questions and the public valuation of different priorities rest with elected officials, planners, and the public towards outlining clear goals in what role subsidized on-demand ride hailing should play.

An important study limitation in the ridership data is the inability to determine who is taking a trip. The individual characteristics of each rider are unknown. The data does not show who the individual riders are, making it impossible to know whether fifty trips represent one person taking fifty rides or fifty different people taking one ride each. As previously noted, the data also masks any entries where less than five rides were undertaken and therefore this information is omitted from this analysis.

CRediT authorship contribution statement

Anne Benaroya: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing. **Matthias Sweet:** Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, Validation, Writing – review & editing. **Raktim Mitra:** Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, Writing – review & editing.

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References

Alemi, F., Circella, G., Handy, S., Mokhtarian, P., 2018. What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California. Travel Behav. Soc. 102 (13), 233–248.

Allen, J., Farber, S., 2019. Sizing up transport poverty: a national scale accounting of low-income households suffering from inaccessibility in Canada, and what to do about it. Transp. Policy 74, 214–223.

Atkinson-Palombo, C., Varone, L., Garrick, N.W., 2019. Understanding the surprising and oversized use of ridesourcing services in poor neighborhoods in New York City. Transp. Res. Rec.: J. Transp. Res. Board 2673 (11), 185–194.

Blodgett, M., Khani, A., Negoescu, D., Benjaafar, S., 2017. Public/Private Partnerships in Transit: Case Studies and Analysis. Minnesota Council on Transportation Access, Minneapolis, MN.

Brown, A., 2019. Redefining Car Access: Ride-Hail Travel and Use in Los Angeles. 85 (2), 83–95.

Calderon, F., Miller, E.J., 2019. A new outlook on ridehailing: spatiotemporal patterns and commuting analysis from the Greater Toronot and Hamilton Area. Procedia Comput. Sci. 151, 745–750.

Centennial Innovation Team, & Fehr & Peers. (2017). *Go Centennial Final Report.* Retrieved from https://www.centennialco.gov/files/sharedassets/public/documents/communications/go-centennial-final-report.pdf.

City of Toronto. (2019). *The Transportation Impacts of Vehicle-for-Hire in the City of Toronto.* Toronto. Retrieved from The Transportation Impacts of Vehicle-for-Hire in the City of Toronto.

Clewlow, R.R., Mishra, G.S., 2017. Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States. UC Davis, Davis, California. Retrieved from https://escholarship.org/uc/item/82w2z91j.

Cochran, A., Chatman, D.G., 2021. Use of app-based ridehailing services and conventional taxicabs by adults with disabilities. Travel Behav. Soc. 24, 124–131.

Correa, D.E., Xie, K., Ozbay, K., 2017. Exploring the Taxi and Uber Demand in New York City: An Empirical Analysis and Spatial Modeling. *Transportation Research Board Annual Meeting.* National Academies, Washington, DC.

Curtis, T., Merritt, M., Chen, C., Perlmutter, D., Berez, D., 2019. Partnerships Between Transit Agencies and Transportation Network Companies. National Academies, Washington, DC. Retrieved from https://nap.nationalacademies.org/read/25576/chapter/1.

de Dios Ortuzar, J., Willumsen, L.G., 2011. Introduction. In: Modelling Transport. John Wiley & Sons, Incorporated, pp. 1–27.

Diab, E., Kasraian, D., Miller, E.J., Shalaby, A., 2020. The rise and fall of transit ridership across Canada: understanding the determinants. Transp. Policy 96, 101–112.

Feigon, S., Murphy, C., 2018. Broadening Understanding of the Interplay Among Public Transit, Shared Mobility, and Personal Automobiles. National Academies, Washington, DC.

Gehrke, S.R., Felix, A., Reardon, T.G., 2019. Substitution of ride-hailing services for more sustainable travel options in the greater Boston region. Transp. Res. Rec. 2673 (1), 438–446.

Ghaffar, A., Mita, S. K., & Hyland, M. (2020). *Modeling Ridesourcing Trip Generation: Chicago Case Study.* Retrieved from https://www.researchgate.net/publication/340595249_Modeling_Ridesourcing_Trip_Generation_Chicago_Case_Study.

Government of Canada, 2016. Dictionary, Census of Population, Primary household maintainer. Retrieved from Statistics Canada. https://www12.statcan.gc.ca/census-recensement/2016/ref/dict/households-menage020-eng.cfm.

Graehler, M., Mucci, A., Erhardt, G.D., 2019. Understanding the Recent Transit Ridership Decline in Major US Cities: Service Cuts or Emerging Modes?. In: Transportation Research Board Annual Meeting. National Academies, Washington, DC, pp. 1–19. Retrieved from.

Grahn, R., Harper, C.D., Hendrickson, C., Qian, Z., Matthews, H.S., 2020. Socioeconomic and usage characteristics of transportation network company (TNC) riders. Transportation (Springer) 47, 3047–3067.

Hall, J.D., Palsson, C., Price, J., 2018. Is Uber a substitute or complement for public transit? 108, 36–50.

Henao, A., Marshall, W.E., 2019. The impact of ride-hailing on vehicle miles traveled. Transportation 46, 2173–2194.

Jin, S.T., Kon, H., Wu, R., Sui, D.Z., 2018. Ridesourcing, the sharing economy, and the future of cities. Cities 76, 96–104.

Lavieri, P.S., Dias, F.F., Juri, N.R., 2018. A model of ridesourcing demand generation and distribution. Transp. Res. Rec. 2672 (46), 31–40.

Lavieri, P., Garikapati, V. M., Bhat, C. R., Pendyala, R. M., Astroza, S., & Dias, F. F. (2017). Modeling Individual Preferences for Ownership and Sharing Autonomous Vehicle Technologies.

Li, W., Shalaby, A., Habib, K.N., 2021. Exploring the correlation between ride-hailing and multimodal transit ridership in Toronto. Transportation.

Lucken, E., Trapenberg Frick, K., Shaheen, S.A., 2019. "Three Ps in a MOD:" role for mobility on demand (MOD) public-private partnerships in public transit provision. Res. Transp. Bus. Manage. 32, 1–10.

Malalgoda, N., Lim, S.H., 2019. Do transportation network companies reduce public transit use in the U.S.? Transp. Res. A Policy Pract. 130, 351–372.

Marquet, O., 2020. Spatial distribution of ride-hailing trip demand and its association with walkability and neighborhood characteristics. Cities 106, 1–10.

Murphy, C., Feigon, S., 2016. Shared Mobility and the Transformation of Public Transit. Transportation Research Board, Transit Cooperative Research Program. National Academies, Washington, DC. Retrieved from.

Palm, M., Farber, S., Shalaby, A., Young, M., 2020. Equity analysis and new mobility technologies: toward meaningful interventions. J. Plan. Lit. 36 (1), 31–45.

Pew Research Center, 2016. The American middle class: Who is in it, and who is not, in U.S. Retrieved from *Metropolitan Areas.* Pew Research Center's Social & Demographic Trends Project. https://www.pewresearch.org/social-trends/interactives/middle-class-metro-map/.

Pike, S., Kazemian, S., 2019. Partnerships between Ridehailing Companies and Public Transit Agencies: An Exploration of Inter-agency Learning about Pilot Programs. University of California Institute of Transportation Studies. ITS Reports.Retrieved from.

Rodier, C., 2018. The Effects of Ride Hailing Services on Travel and Associated Greenhouse Gas Emissions. National Center for Sustainable Transportation, Davis, CA. Retrieved from https://escholarship.org/uc/item/2rv570tt.

Sather, M., 2018. New Model for Transit: Transit/TNC Partnerships in Western Riverside County. UCLA Institute of Transportation Studies, Los Angeles. Retrieved from https://escholarship.org/uc/item/4fj458xx.

Schwieterman, J., Livingston, M., van der Slot, S., 2018. Partners in Transit: A Review of Partnerships between Transportation Network Companies and Public Agencies in the United States. Depaul University, Chaddick Institute for Metropolitan Development at Depaul University. Retrieved from https://www.researchgate.net/publication/328575814_Partners_in_Transit_A_Review_of_Partnerships_between_Transportation_Network_Companies_and_Public_Agencies_in_the_United_States.

Shi, E., Sweet, M., 2020. Who uses ride-hailing? Using cluster analysis to identify traveler markets in the greater Toronto and Hamilton area. Can. Geogr. 1–23.

Sikder, S., 2019. Who uses ride-hailing services in the United States? Transp. Res. Rec. 2673 (12), 40–54.

DTMI Spatial, Inc. (2016). *Enhanced Points of Interest (EPOI).*

Thomas, G.C., Clewlow, R.R., Connor, M., Cruz-Casas, C., Feigon, S., Hall, J., Steudle, K. T., 2021. The Role of Transit, Shared Modes, and Public Policy in the New Mobility Landscape. National Academies, Washington, DC. Transportation Research Board.

Tirachini, A., 2020. Ride-hailing, travel behaviour and sustainable mobility: an international review. Transportation 47, 2011–2047.

Town of Innisfil, 2017. Demand-Responsive Transit Implementation - Stage 1. Retrieved from, Town of Innisfil https://learn.sharedusemobilitycenter.org/wp-content/uploads/dsr-042-17_demand-responsive_transit_implementation_-_stage_1_id_210934_-_pdf.pdf.

Town of Innisfil, 2018. Innisfil Transit: Launch of Stage 2. Town of Innisfil, Land Use Planning. Retrieved from https://innisfil.ca/wp-content/uploads/2019/05/DSR-028-18-Innisfil-Transit_-Launch-of-Stage-2-Pdf.pdf.
Town of Innisfil, 2019. Innisfil Transit—2018 Results and Fare Changes. Innisfil, ON. Retrieved from https://innisfil.ca/wp-content/uploads/2019/05/DSR-038-19-Innisfil-Transit-2018-Results-and-Fare-Changes-Pdf.pdf.
Town of Innisfil, 2020. Innisfil Transit—2020 Results and Updates. Retrieved from. https://innisfil.civicweb.net/FileStorage/190AF741D3D049D7930D370BBFA60464-Innisfil%20Transit%20-%20Update.pdf.
Town of Innisfil, 2021. Innisfil Transit—2020 Results and Updates. Retrieved from, Innisfil https://innisfil.civicweb.net/FileStorage/67E5E5EC62774DFB89763D9B08AAE73E-Innisfil%20Transit%20-%202020%20Results%20and%20Updates.pdf.
United States Federal Transit Administration, 2020. Mobility on Demand (MOD) Sandbox Program. United States Government.
Young, M., Allen, J., Farber, S., 2020. Measuring when Uber behaves as a substitute or supplement to transit: An examination of travel-time differences in Toronto. J. Transp. Geogr. 82, 1–11.
Young, M., Farber, S., 2019. The who, why, and when of Uber and other ride-hailing trips: An examination of a large sample household travel survey. Transp. Res. A 119, 383–392.
Yu, H., Peng, Z.-R., 2019. Exploring the spatial variation of ridesourcing demand and its relationship to built environment and socioeconomic factors with the geographically weighted Poisson regression. J. Transp. Geogr. 75, 147–163.