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Evaluating the Influence of Ride Sourcing Services on Travel Patterns and Transportation Networks in Toronto

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Abstract: This study provides a detailed analysis of the evolving impact of ride-sourcing platforms such as Uber and Lyft on travel behavior and mobility patterns within Toronto. Utilizing origindestination data from approximately 100 million trips recorded between 2016 and 2019, we examine spatial and temporal trends in ride-sourcing activities. Our methodology integrates these data with car travel times, public transportation networks, and city regulations to assess the influence of ride-sourcing on overall traffic flow, public transit usage, and cyclist safety. Through route analysis and trip linkage techniques, we estimate that ride-sourcing vehicles contributed to 5–8% of the total daily vehicle kilometers traveled (VKT) in September 2018—approximately double the figures from October 2016. While ride-sourcing activity surged, our findings indicate that downtown travel times remained largely stable. Additionally, curbside pick-up and drop-off patterns highlight the necessity for improved curb management strategies to enhance safety and efficiency. These insights provide a foundation for future policy decisions regarding urban mobility and ride-sourcing regulation.

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I. INTRODUCTION

The growth of ridesourcing companies (alternatively ridehailing companies or transportation network companies (TNCs)) such as Uber and Lyft across North American cities over the past decade has led to enormous and rapid changes in travel behavior. In March of 2019, an average of 770,000 ridesourcing trips were performed daily in New York City [1] and 330,000 in Chicago [2]. Despite its prevalence, how ridesourcing contributes to congestion, impacts other road users, interacts with public transportation and affects transportation equity all remain topics of active debate amongst researchers, city planners and policy-makers. This is in part because details and data records of ridesourcing company operations are generally kept private, forcing researchers touse novel means of collecting them, such as scraping vehicle position data using APIs provided by the companies ([3]) or even driving for the companies themselves ([4]). Consequently,cases where companies volunteer disaggregated trip data or submit it for regulation (eg. [5]; companies in New York City [6]) make for unique opportunities to build comprehensive pictures of how they operate within a city.

Uber first started offering its UberX service in Toronto, Canada, in September 2014. In response to growth in ridesourcing activity, in July 2016, the City of Toronto amended the Vehicle-for-Hire (VFH) Bylaw [7] that regulates taxis and limousines to enable ridesourcing services to operate in the city by September 2016. This bylaw requires ridesourcing companies to report individual trip origin-destination (OD) data to the city. Lyft followed Uber into the Toronto market at the end of 2017.

In 2018, the City undertook a comprehensive review of the bylaw, which included a study on the transportation impacts of ridesourcing in Toronto. The study, a collaboration between the Big Data Innovation Team within the City of Toronto'sTransportation Services Division and the University of Toronto Transportation Research Institute (UTTRI), was published in June 2019 [8].

This paper is a companion article to the study, and will summarize its most important findings regarding congestion impact and curbside impacts. A critical dataset for understanding localized congestion impacts was not provided to the City by ridesourcing companies: the volume of vehicles on streets. We therefore developed a novel process to estimate volumes by routing ridesourcing passenger trips and modelling driver behaviour between those trips. Detailing and validating this process will be the primary focus of the methodology. Research conducted by UTTRI for this study are detailed in other TRB submissions including a travel behavior survey [9], a study on transit alternatives to ridesourcing [10], a regression on transit ridership [11], and a ridesourcing service provision model [12].

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II. LITERATURE REVIEW

Transportation agencies have historically operated with limited data on ridesourcing companies' operations. The San Francisco County Transportation Authority (SFCTA) performed their study by scraping data from the APIs of Uber and Lyft, a technique which is unlikely to ever be replicated because these companies have since restricted this access [3]. By comparing traffic speeds with a traffic model with and without the presence of ridesourcing companies in San Francisco, they determined that 30% of the increase in congestion can be attributed to ridesourcing vehicles [13]. New York City has conducted multiple studies on the congestion impacts of ridesourcing: in 2016 finding that while ridesourcing operations contributed to congestion, other factors had contributed more to recent speed decreases in Manhattan [14]. In 2019, a study using video data collection found that ridesourcing companies make up 30% of vehicle miles travelled (VMT) in downtown Manhattan [6]. Cities such as New York City, Chicago, and Sao Paulo are now requiring detailed trip record data. Our study is the first based on OD trip records provided to a City, and the first to examine in detail such a long period of growth in ridesourcing trips.

III. METHODS

This section describes our sources of data and our data reduction methods.

A. Data Sources

The study relied primarily on seven data sources:

- **Ridesourcing trip records:** ridesourcing companies submit individual trip records to the City, including origin, destination, request and pick-up timestamps, ride duration, distance, type of service (wheelchair-accessible, Uber XL, etc.), ridesplitting trip segment ID, and trip status - whether the trip was cancelled by either driver or passenger. Origin and destination locations are snapped to the nearest intersection in the City's street centreline dataset [15]. Records from September 7, 2016 to September 30, 2018, were made available. After March 30, 2017, request time and trip status were no longer available in trip records, and pick-up timestamps were truncated to the nearest hour. Aggregate records for late 2018 and 2019 were also provided.
- **Supplementary aggregate ridesourcing statistics:** by our request, a subset of ridesourcing companies provided additional information including the number of active drivers per hour for selected days, average fraction of VKT while in-service and while deadheading aggregated over all vehicles in March 2017 and September 2018, and additional aggregated wait time data after April 2017.
- **Ridesourcing pick-up and drop-off data**: pick-up and drop-off counts at a 10m resolution - significantly more precise than the trip record OD data - were acquired using SharedStreets [16] as a broker in partnership with ridesourcing companies. The data is aggregated by hour and spans a total of 9 weeks from January to September2018.
- **Historical travel speed data:** travel speed data from September 2016 - October 2018 was provided by HERE Technologies for all available street segments; data represents the mean speed along road segments for 5-minute increments. Speed data from October 2017 - March 2019 was also acquired from the City's system of Bluetooth sensors along downtown arterial streets. This data is also in 5-minute increments, for road segments that span between major intersections. The HERE data covers the entire city and is used to estimate historical street networktravel times.
- **2016 Transportation Tomorrow Survey (TTS):** the TTS is a regional household travel survey conducted by the University of Toronto in collaboration with local and provincial government agencies. The survey collects demographic, travel behavior and travel mode information. The most recent survey was in 2016.
- **Ridesourcing travel behavior survey:** a survey wasundertaken by UTTRI in May 2019 to collect information from a market research panel on their revealed and stated transportation mode preferences for commute and noncommuter trips. The survey's authors discuss their work in [9].
- **Street-linked vehicle volumes:** the output of the 2016 KCOUNT model described in [17] are Annual Average Daily Traffic (AADT) volumes mapped to the City's street centreline network.

Trip records, pick-up/drop-off data and historical speed data were hosted on a PostGIS geospatial object-relational database (running on PostgreSQL 9.6) [18], [19].

B. Methodology for Processing Curb Activity

Pick-up/drop-off (PUDO) data was provided with Shared- Streets reference IDs. The city's bikelane network was mapmatched to the SharedStreets network using their street segment matching toolkit in order to aggregate activity by bikelane segment [20].

C. Methodology for Estimating Vehicle Volumes on Streets

As described in [4], ridesourcing drivers cycle between three phases when serving multiple trips over their work period:

- Cruising while waiting to be matched with a passenger;
- Driving en-route to a pick-up once matched; and
- Driving in-service of the passenger.

Cruising and driving en-route are both forms of deadheading (driving without a passenger). At the beginning and end of the work period, the driver may also "commute" - deadhead from and to another location such as a residence or place of work. All of these behaviours contribute to VKT on streets.

The ridesourcing trip records include the in-service VKT, but not deadheading VKT, nor were vehicle IDs or disaggregated wait times available. In order to localize in-service VKT to specific areas of Toronto, we modeled the likely paths drivers took from origin to destination for in-service activity. To estimate time and VKT spent

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deadheading, we also linked the destinations of trips with the origins of subsequent trips in such a way that best reproduces the empirical distribution of passenger wait-times, and modeled the likely paths drivers took to complete these connections.

Due to the computational demands of this process, it was used on data from two days out of the study period: October 20, 2016 with 64,800 trips and September 13, 2018 with 140,900 trips, both of which are within 8% of the average daily number of trips in their respective months, and thus are representative of typical days near the beginning and end of the study period. As request data was only available before April 2017, October 20 was also used for testing, calibration and validation.

➢ *Trip Routing for in-Service Activity:*

To assess inadministration trip directions, we steered each excursion from beginning to objective utilizing pgRouting [21], a PostGIS [19] execution of Dijkstra's Most limited Way calculation. Trips were directed through a road network weighted utilizing HERE movement speed information for the 5-minute time frame in which excursions began. Holes in rush hour gridlock information were filled in by utilizing information models gave by HERE to every road portion by season of week.

Our steering strategy was:

- *Generate a Routing Network:*

For every five-minute receptacle, we joined authentic traffic information for that time with models for that day of week, 15-minute time frame and connection given by HERE. Interface IDs were copied for bidirectional roads and yet again attracted the course of movement. Source and target hubs for each connection were likewise rectified to the bearing of movement. The organization generally represents access limitations furthermore, contrasts in street rise however doesn't represent turn limitations at convergences. The city's centreline network, to which vehicle volumes are planned, was map-matched to the HERE network utilized for steering utilizing the Shared- Streets [20] tool compartment in request to guarantee comparative roads networks were utilized to compute ridesourcing VKT as an extent of complete City VKT.

- *Prepare Trip Records for Routing:*

✓ **Trips within Toronto:** for each excursion record, the closest hub was tracked down in the routable HERE organization. These were regularly the identical crossing points.
✓ **Trips to/from outside of Toronto:** for trip records where the beginning or on the other hand objective was outside the city however inside the six closest districts, the hub was relegated to be a Toronto crossing point on that district's line illustrative of a significant blood vessel or interstate. Trips from or to past the six closest districts (addressing 0.3% of all excursions) were rejected from directing.
✓ **Generate Shared Ride Segments:**Ridesplitting trips - where a few excursions with various starting points and objections are served at the same time by one vehicle - were re-requested into fragments addressing stops the ridesourcing driver would have made in sequential request.
✓ **Impute Timestamps:** Trip record timestamps after Walk 30, 2017 were moved to the beginning of great importance (for instance 2018-09-13 07:47:00 becomes 2018-09-13 07:00:00). For these, we ascribed more exact get timestamps by haphazardly testing from other pick-ups inside a one kilometer sweep for a similar date and hour from trip records gave to us independently by a ridesourcing organization. The drop-off timestamp was then, at that point, determined from the length of the excursion gave at brief goal.

- *Route Trip Records:*

Five-minute clusters were shipped off a many-numerous Dijkstra steering motor with the organization for that time span in clusters of 250 extraordinary starting points and their relating objections (because of memory restrictions). The directing motor returns the briefest way for every OD pair given traffic conditions around then.

- *Determine Volumes on Streets:*

Vehicle volumes over a period of time were calculated for each segment of the routing network by summing up the number of paths that include the segment during this period. The corresponding total VKT was determined by multiplying the vehicle volume by the segment length. Neighbourhood ridesourcing VKT was then factored by the ratio of aggregate routed distance and the network distance of reported trips for the entire city.

Our code for routing trips is available at https://github.com/CityofToronto/bdit triprouter.

➢ *Trip Linking for Deadheading:*

There is a paucity of information in the trip records concerning any of the phases of deadheading – commuting, cruising or en-route driving.

Without vehicle trajectories, predicting driver behavior while cruising is quite difficult, since there are many actions they could take. [22] and [4] report some drivers pull over while others circle in place or drive over to areas they deem lucrative. Ridesourcing companies use dynamic pricing to balance their vehicle supply with demand, partly from incentivizing their drivers to move to high-demand areas through these higher prices [23], [24]. Dynamic pricing will heavily affect cruising behaviour, but details of their implementation and effectiveness are not publicly disclosed. Meanwhile, it is extremely difficult to quantify ridesourcing drivers commuting, since they may have their ridesourcing driving app turned off, and may also incorporate travel they would had done independent of their ridesourcing work.

In order to estimate deadheading, then, we make the simplifying assumption that drivers immediately pull over after dropping off their previous passenger, and once matched

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with a new passenger drive over to their pick-up via the shortest travel-time route. We then can route en-route travel with the same algorithm used to route in-service trips. This ensures we have a conservative estimate for VKT during deadheading. We also do not consider the additional time required for the ridesourcing company to match drivers and passengers, or the time between drivers arriving at a passenger pick-up point and the start of the trip, as these cannot be effectively estimated from the trip records.

To connect trips together into sequences, a process we refer to as “trip linking”, we adopt the methodology of [25] and [26]. Both cast the problem of assigning drivers to trips as finding a solution on a bipartite graph of feasible connections between the two groups. Feasible connections are found by calculating travel times between driver positions and trip pickup points, and keeping those that are smaller than some limit δ. In particular, [25] forgo explicitly modeling vehicles by finding feasible connections between trip drop-offs and subsequent trip pick-ups by checking if the en-route travel time between them is shorter than both the time between drop-off and pick-up as well as δ. They then select a set of feasible connections such that each drop-off is connected to at most one pick-up. They interpret sequences of connected trips – “paths” – as sequences of trips serviced by an individual driver. Because every path (including ones with only one trip) must be serviced by a driver, the size of the vehicle fleet is an outcome of their model and does not need to be specified. Moreover, while only en-route time is utilized to determine feasibility, the time between drop-off and pick-up must be equal to both the enroute and cruising times, so this methodology also outputs a cruising time estimate.

We adopt [25]’s notation and methodology. In particular, we implement their “batch” methodology, which breaks V into sub-graphs representing short periods of time t_{batch}:

- *Generate a Dataset of Feasible Links:*

We first converted trip records into a set of feasible connections from trip drop-offs to pick-ups over a 24 hour period. Feasible connections wer found by binning drop-off points into five-minute intervals. For each drop-off, up to 30 of the closest pick-up points of trips beginning within the subsequent 20 min and 5km are found (values chosen to make the calculation computationally tractable on our database system). The arrangement of all drop-offs were then directed to the arrangement of all pick-ups utilizing the excursion directing method from a higher place. All courses that take more time to go than the time contrast between the drop-off and get were disposed of. The leftover courses address possible connections between drop-offs and pick-ups, with a most extreme in transit travel time $\delta \approx 20$ min.

- *Transform the Feasible Links into a Graph*

V (N,E) the feasible links were then transformed into a directed acyclic graph V (N,E) where nodes N = {n} represent trips and edges E = {e} represent the feasible connections, whose weights are the en-route travel times from Step 1. We define a path P in V (N,E) to be a sequence of edges that connect a sequence of nodes together such that no node has more than two adjacent edges belonging to the path; these represent the trips taken over a driver’s work period. There may be zerosize P that correspond to single unconnected trips. A set of paths {P} where every node is included, but a node is only associated with one (possibly zero-size) path, is known as a (node-disjoint) path cover. It represents the trip sequences serviced by a population of drivers over the course of the day. Alongside V (N,E), we initialized a **solution graph** S(N, ∅), which has the same nodes as V , but no edges. This stores the path cover.

- *Link Sections of V in Order of Time:*

We broke the day up into consecutive time bins each of width t_{batch}, and, in time-order, perform the following for each bin:

- ✓ **Create a subgraph** V_b, which consists of a set of trip $\{n\}_b$ with pick-up times between t and $t + t_{batch}$, and all previous trips $\{n\}_{lb}$ that have feasible links to those in ns. $\{n\}_{lb}$ trips may have drop-off times earlier than t.
- ✓ **Transform V_b into a bipartite graph:** following, we converted V_b into a bipartite graph $\hat{V}b$ by splitting each node n into the trip drop-off n^d and pick-up n^o, then mapping the edges of V_b onto these new nodes such that an edge connecting n_i and n_j in V_b connects $n^d{}_i$ and $n^o{}_j$ in $\hat{V}b$. Finding a path cover in V_b is equivalent to finding a matching– a subset of edges such that each node has only one adjacent edge – in $\hat{V}_b$ [25].
- ✓ **Find a matching for the bipartite graph:** we then used one of several algorithms to determine a matching within $\hat{V}_b$. These are detailed below. Once a matching was found, it was converted back into a path cover in V_b.
- ✓ **Transfer the path cover onto S, and prune V** : the edges of V_b were transferred to S. Nodes with new outgoing edges in S had their outgoing edges in V removed, so that these nodes are not included in future subgraphs.

- *Determine Volumes on Streets:*

Once solution S was complete, we converted the path cover back to a set of en-route trips and corresponding volumes on streets.

The matching algorithms we tested are:

- ✓ **Maximum cardinality matching:** find a bipartite graph matching with as many edges as possible. This is equivalent to determining the minimum number of drivers required to service all trips within a time bin [25]. Our implementation uses the bipartite maximum matching function from network
- ✓ **Minimum weight maximum cardinality matching:** unlike the above algorithm, which does not take edge weights into account, this produces a maximum cardinality matching whose network weights are minimized. Effectively, this algorithm first minimizes the number of drivers, then optimizes their trip assignments to minimize the total en-route time. We implemented this as a minimum flow assignment problem using Google OR-Tools

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- ✓ **Greedy matching:** connect each pick-up with the available drop-off with the shortest en-route time, handling the pick-ups in order of time. Drop-offs that are connected to pick-ups are no longer available to be connected with future pick-ups. This is a simplified version of Uber's driver-passenger matching algorithm [26], [24]. Since trips are linked individually by order of pick-up time, a solution was calculated on the entire graph V , rather than through batching.

Our code for generating feasible links is available in bdit_triprouter, while the code for trip linking is available at https://github.com/CityofToronto/bdit triplinker.

Since trip linking is a highly simplified model of how drivers are connected with passengers using limited data, it cannot be used to reconstruct the exact service history of individual drivers. Our aim is instead to produce a set of trip linkages that, in the aggregate, resembles real-life en-route deadheading.

- ➤ *Trip Linking Calibration:*

We calibrate trip linking by selecting the combination of matching algorithm and param eters that best reproduces the distribution of passenger wait times in the trip records on October 20, 2016. The two tunable are δ and (except for greedy matching) tbatch. We used a Bayesian hyperparameter optimizer to tune these for each of the matching algorithms, using the Jensen-Shannon divergence between the recorded and trip linking distributions of passenger wait times as an objective function. Distributions from the optimally calibrated algorithms are compared with the reported distribution in Figure 1.

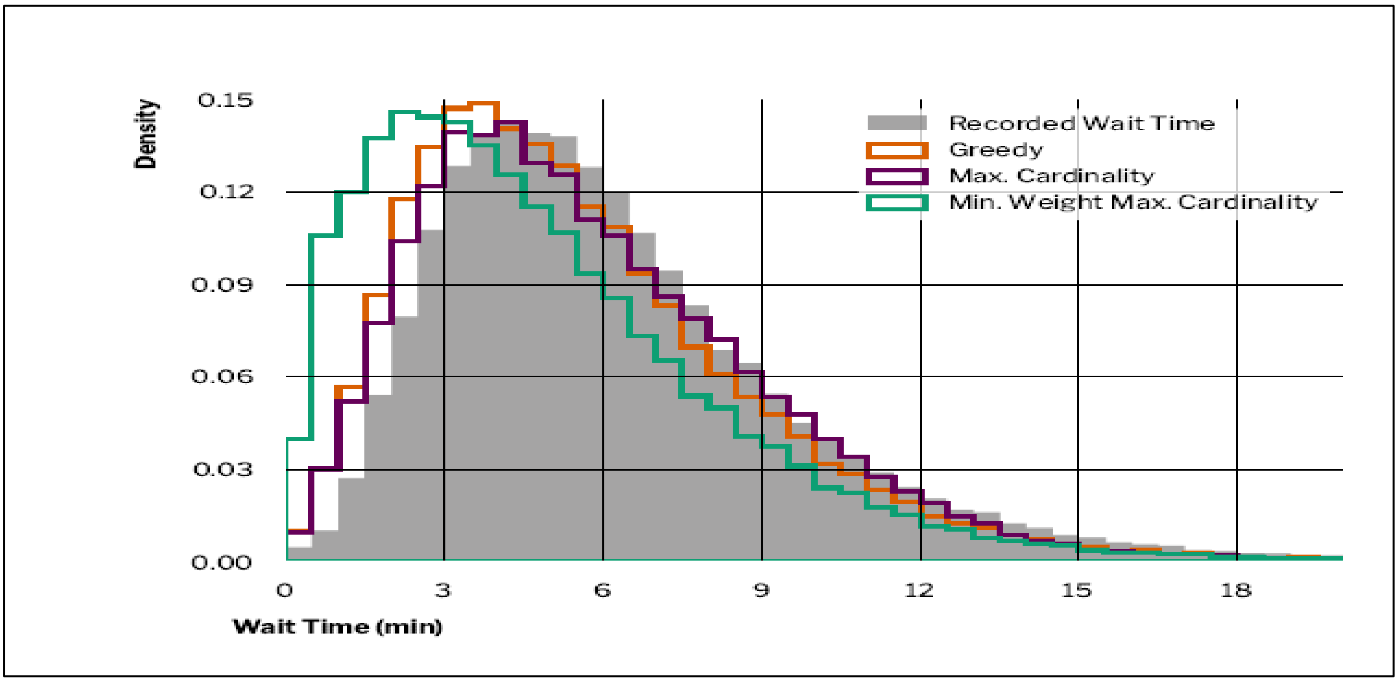

Fig 1 Recorded Distribution of Passenger Wait Times on October 20, 2016, Compared with ones Calculated from Trip Linking using Different Matching Algorithms.

For both maximum cardinality and greedy matching, we found the optimal δ to be as large as possible (≈ 20 min, as mentioned in the methodology). For maximum cardinality, the optimal tbatch is as small as possible (1 min, as timestamps after April 2017 are at best accurate to the minute). Interestingly, the minimum weight maximum cardinality matching produced a distribution of wait times offset by ∼ 1.5 min from the reported distribution regardless of the tuning parameter values. Between the three matching algorithms, maximum cardinality produced a distribution closest to the recorded one, and so was selected to produce our final results in Figure 4. Since no wait time data was available for September 13, we use the same parameters as for October 20.

D. Testing and Validating the Volume Estimation Process

- ➤ *Validating Trip Routing:*

Trip routing was validated by comparing routed distance with distance in the ridesourcing trip records.

For October 20, 2016, the fractional difference between recorded and routed distance is −8% } 17%. Both these values change by ≲ 4% if only trips greater than the median distance, trips within downtown Toronto, or trips during peak commuting hours (7:00 - 10:00 a.m. and 4:00 - 7:00 p.m.), are considered. The discrepancy can partly be explained by the lack of turn restrictions, and partly by routing not capturing real-world complications like queuing to turn at intersections, or circling to find an appropriate curbside location to drop-off a passenger. The standard deviation is also inflated from ∼ 6% of trips where the fractional difference is greater than

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−33%. Some of these appear to be tours of errands returning to their origin.

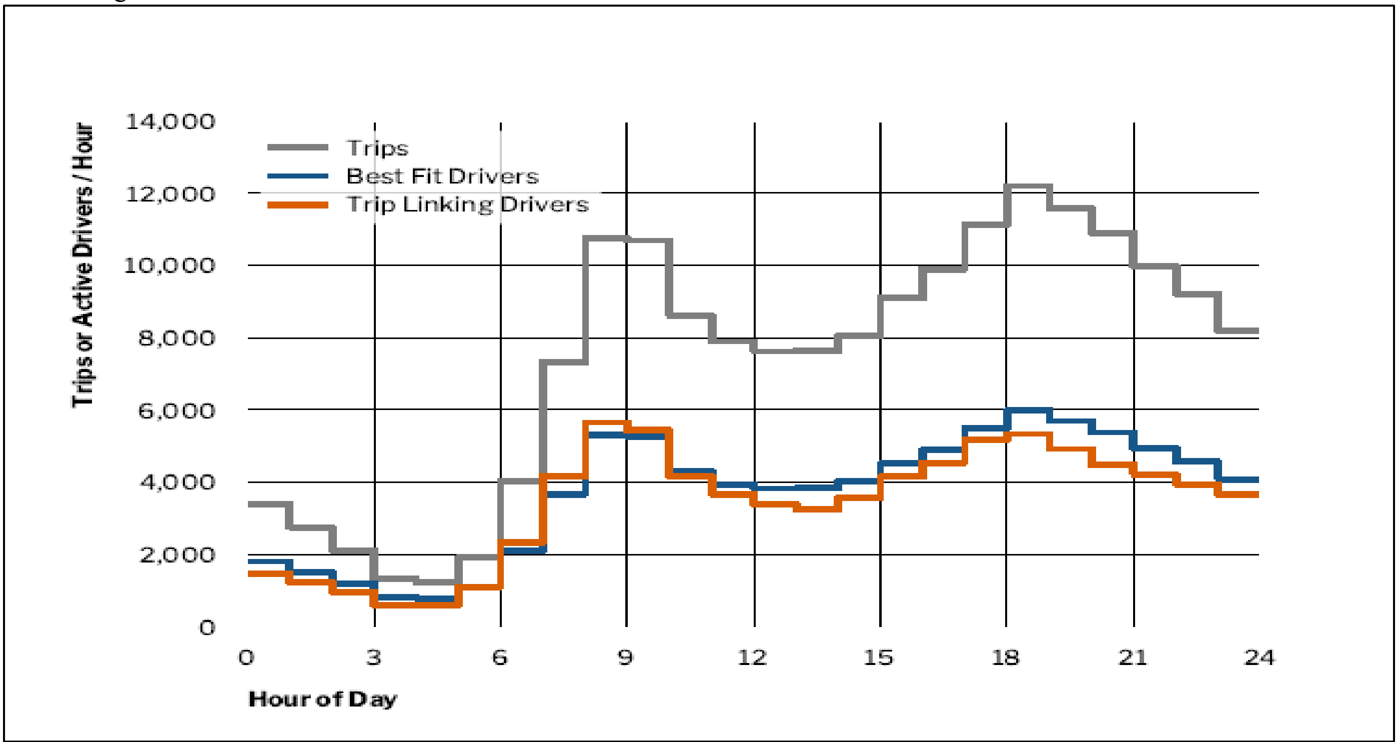

Fig 2 The Number of Trips per Hour on September 13, 2018 and the Number of Unique Drivers per Hour Servicing the Trips as Estimated by a Best Fit to the Empirical Data (Equation 1) and trip Linking using the Maximum Cardinality Matching Algorithm.

To reduce the fractional difference between linked and recorded results, we aggregated to the Toronto neighbourhood level (~ 2 km across). The fractional difference between recorded and routed aggregate VKT within different neighbourhoods is −7 ± 2 (−6 ± 4 for morning commuting hours and −8 ±4 for afternoon commuting).

➢ *Validating Trip Linking:*

Trip linking was validated by comparing features of the generated results with reported values from the ridesourcing companies.

- *Number of Unique Drivers per Hour –:*

A subset of ridesourcing companies provided the number of unique drivers per hour for a set of 39 days from December 2017 – March 2019. An ordinary least squares regression of the number of active drivers versus the number of trips gave:

$$N_{Drivers} = 0.475N_{Trips} + 199.1 \quad (1)$$

(adjusted R^2 = 0.962; RMS deviation = 274.7). This is equivalent to about two trips per driver per hour, though it does not account for drivers working for multiple ridesourcing companies and therefore slightly overestimates the number of drivers required to service trips from all companies in an hour.

In Figure 2, we show the number of trips per hour on September 13, 2018, and compare the number of unique drivers predicted by Equation 1 and by trip linking. Trip linking reproduces well the two-humped shape of the best fit curve, but on average predicts ~ 10% fewer drivers per hour, which in the evening peak is a deficit of ~ 500−800 drivers. The trip linking driver number estimate for October 20, 2016 is also several hundred fewer drivers than the best fit one, but since there were only half as many trips on October 20 as there were on September 13, the fractional deficit is ~ 25%.

- *Deadheading as a Fraction of Total Activity –:*

A subset of ridesourcing companies also provided the fraction of their fleetwide aggregate VKT spent deadheading, reporting that 55% of total VKT is for in-service driving, 35 − 40% is cruising, and 5 − 10% en-route driving. This means for each kilometer driven in-service, drivers typically travel an additional 0.6 − 0.7 kilometers cruising, and 0.1 − 0.2 kilometers en-route to their next trip.

The ratio of aggregate en-route to in-service VKT from maximum cardinality trip linking is 0.15 for both October 20, 2016 and September 13, 2018, consistent with the ridesourcing companies records. However, the records show that deadheading is dominated by cruising, and while trip linking does not calculate a cruising VKT, we can estimate it by assuming the ratio of aggregate cruising to in-service time is roughly the same as the ratio of distances. The time ratios are sensitive to linking algorithm choice, and for September 13, 2018 range from 0.16 for maximum cardinality to only 0.09 for greedy matching. Regardless of algorithm, though, the ratio is always far lower than reported by the ridesourcing companies. Note that it is unclear whether they includes drivers making trips unrelated to ridesourcing while keeping their ridesourcing app open, which would inflate their cruising fraction.

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E. Assessing the Volume Estimation Process

Given that we did not have to specify anything about the size or behavior of the ridesourcing driver population, it is remarkable that trip linking is able to approximate both the passenger wait time distribution (Figure 1) and number of drivers per hour (Figure 2). That said, all combinations of linking algorithms and parameters underestimate the median passenger wait time by at least 20 sec, and the number of drivers by at least 10%. Moreover, it grossly underestimates the time vehicles spend cruising. All these point to trip linking significantly underestimating deadheading time and VKT. We therefore caution that our volumes on streets estimates are conservative.

It is possible that some of the assumptions underlying trip linking lead to unrealistic minimization of deadheading – most notably, the minimum weight maximum cardinality algorithm leads to a significant underestimate of the passenger wait time (Figure 1). One way of more realistically modelling ridesourcing inefficiencies would be to treat drivers as agents that stop working after a set time, or after a particularly long trip. Currently there is no maximum length of time for a work period, and 10% of periods from October 10, 2016 are longer than 4.6 hrs. Another possibility is that we need to explicitly model cruising behaviour – perhaps circling or driving to another neighbourhood during cruising lengthens its duration. Implementing these features is a promising avenue for future work, though more empirical data on ridesourcing driver behaviour is required.

One reason we believe agent-based modelling is promising is the work of [12], who developed a prototype ridesourcing provision model using the ridesourcing trip records. Their model is agent-based, and uses recorded trip request times to link drivers and passengers, without requiring that the driver also arrive at the recorded pick-up time. They also instantiate drivers randomly throughout the city for deadheading before the first trip, and use a different method to determine en-route travel times than we do. While our method is better able to reproduce the recorded passenger wait time distribution, their aggregate fractional VKT values – 39% cruising, 19% enroute and 42% in-service – are much closer to trip record values, and they are able to roughly reproduce wait times and drivers per hour using fewer trip record attributes than we do. A comparative study will be required to understand which differences between our models is most responsible for producing these differences.

IV. RESULTS

This part features the critical outcomes from our investigations, focussing on clog and curbside action.

Ridesourcing trips have developed quickly since September 2016, when the help was first authorized by the City. A normal of 176,000 outings were made day to day in Walk 2019, an increment of more than 180% since September 2016. As of Walk 2019, 105 million ridesourcing trips have been finished in the City of Toronto.

➢ *Ridesourcing Trip-Production Tops are Seen in Two Particular Time Spans:*

- **Friday and Saturday Nights:** the most active time frames are Friday and Saturday evenings, topping at a typical 13,100 excursions each hour at 12 PM on Sunday morning. This time span is commonly connected with nightlife movement, which is reflected in the predominance of excursions in the midtown Amusement Region during this time.
- **Weekday Driving Periods:** ridesourcing is vigorously utilized in the first part of the day also, evening top periods, regularly connected with the times during which the street network encounters the most traffic. This outing market has expanded throughout the course of recent years.

➢ *Ridesourcing Trips are more Commuter-Focused outside of Downtown*

Worker trips are arising as a significant excursion market that are by and large progressively caught by ridesourcing. This is represented in Figure 3, which shows a scene with two unmistakable topographies: downtown areas for the most part see multiple Friday and Saturday night trips (7 p.m. to 3 a.m.) for each work day suburbanite period (work days 7 a.m. to 10 a.m. what's more, 4 p.m. to 7 p.m.) trip while the inverse is valid in suburbia where excursions are significantly more worker centered. Figure 3 likewise thinks about the normal hourly pick-ups by hour of week for September for the midtown locale of Toronto and East York, and the three rural areas consolidated. Trip rates are comparative between the two geologies non-weekend days from 4 a.m. until 8 a.m., when they top in suburbia. Around half of these excursions are to the closest metro station (10%) or inside their locale (40%), the other half are to other rural areas (40%) or to downtown (10%). This exhibits that a part of ridesourcing administration is carrying travelers to metro administration while lightening worries that they are empowering huge volumes of suburbanites to be driven midtown during the pinnacle.

For trips starting downtown, the a.m. peak occurs an hour later at nearly 5,000 trips/hr. This is also an hour later than peak transit ridership according to the Transportation Tomorrow Survey [10]. This is when ride-sourcing is least competitive with transit, with travel time savings of on average 8 min/trip. 73% of these trips would have been one-seat rides had they been taken [10].

The suburban afternoon peak is as high as the morning peak if a little wider. Downtown the afternoon peak continues into the evening, bolstered by evening entertainment trips.

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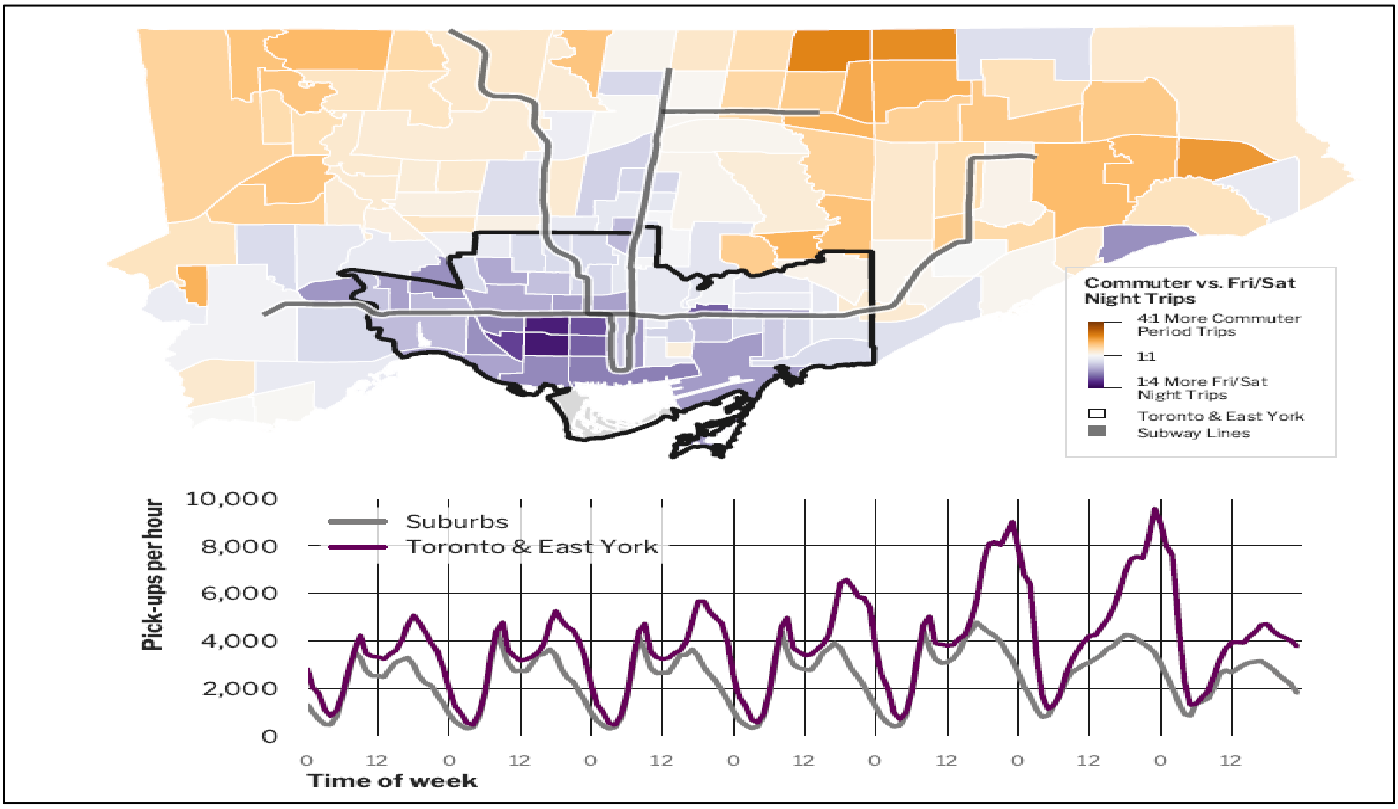

Fig 3 Average ridesourcing pick-ups by neighbourhood and time in September 2018. Above: a map of the ratio of commuter to Friday/Saturday night trips. The district of Toronto East York is outlined in black, and the subway system in gray. Below: number of pick-ups per hour within and outside of Toronto East York over the course of the week.

- *Ridesourcing in Downtown Toronto make up 5-8% of Total Traffic*

Figure 4 shows our modest approximation of ridesourcing volumes which does exclude cruising gauges. The biggest volumes of ridesourcing vehicles are thought midtown where they represent somewhere in the range of 5 and 8% of generally day to day traffic in midtown neighborhoods. The most active area is Waterfront People group The Island, which incorporates major transportation hubs like Association Station and Billy Priest Air terminal.

On this day, ridesourcing represented around 1,230,000 VKT. This is assessed to be 1.9% of the absolute 67,200,000 VKT went in Toronto by and large. The extent of traffic in a.m. furthermore, p.m. top driving periods is marginally lower than the general day to day aggregates, mirroring the higher relative ridesourcing volumes that happen during night hours.

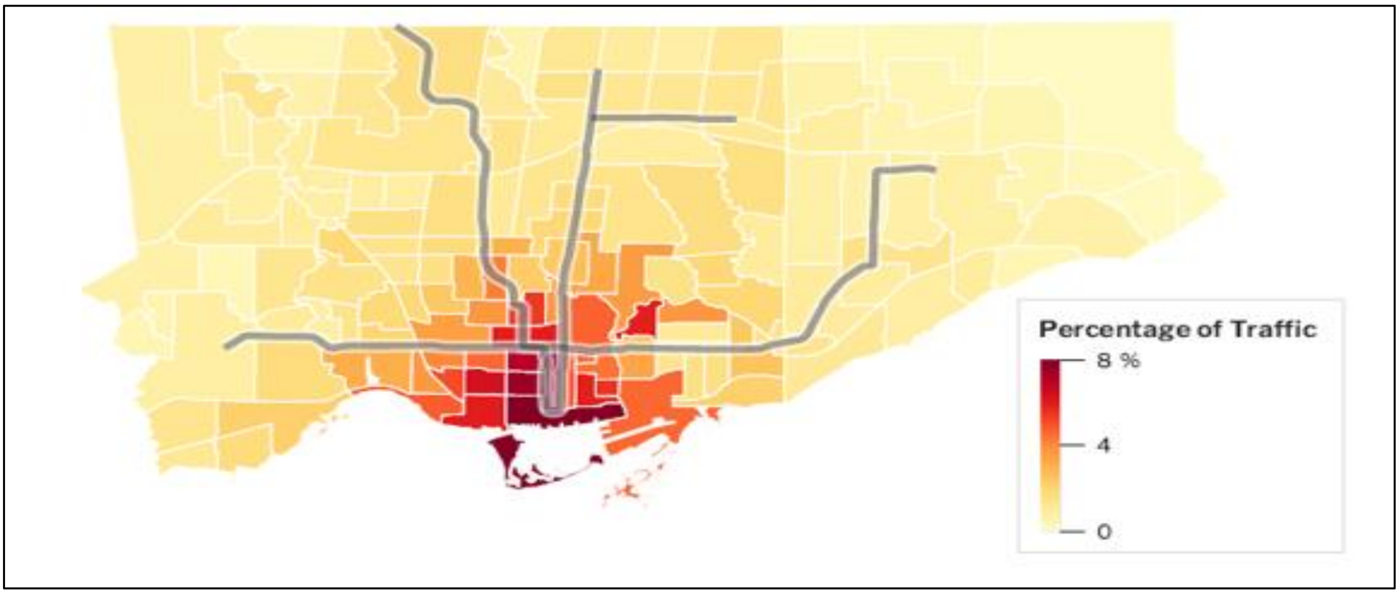

Fig 4 Percentage of Total City VKT due to Ridesourcing Activity for September 13, 2018. Only in-Service and en-route VKT are Included (see Methods)

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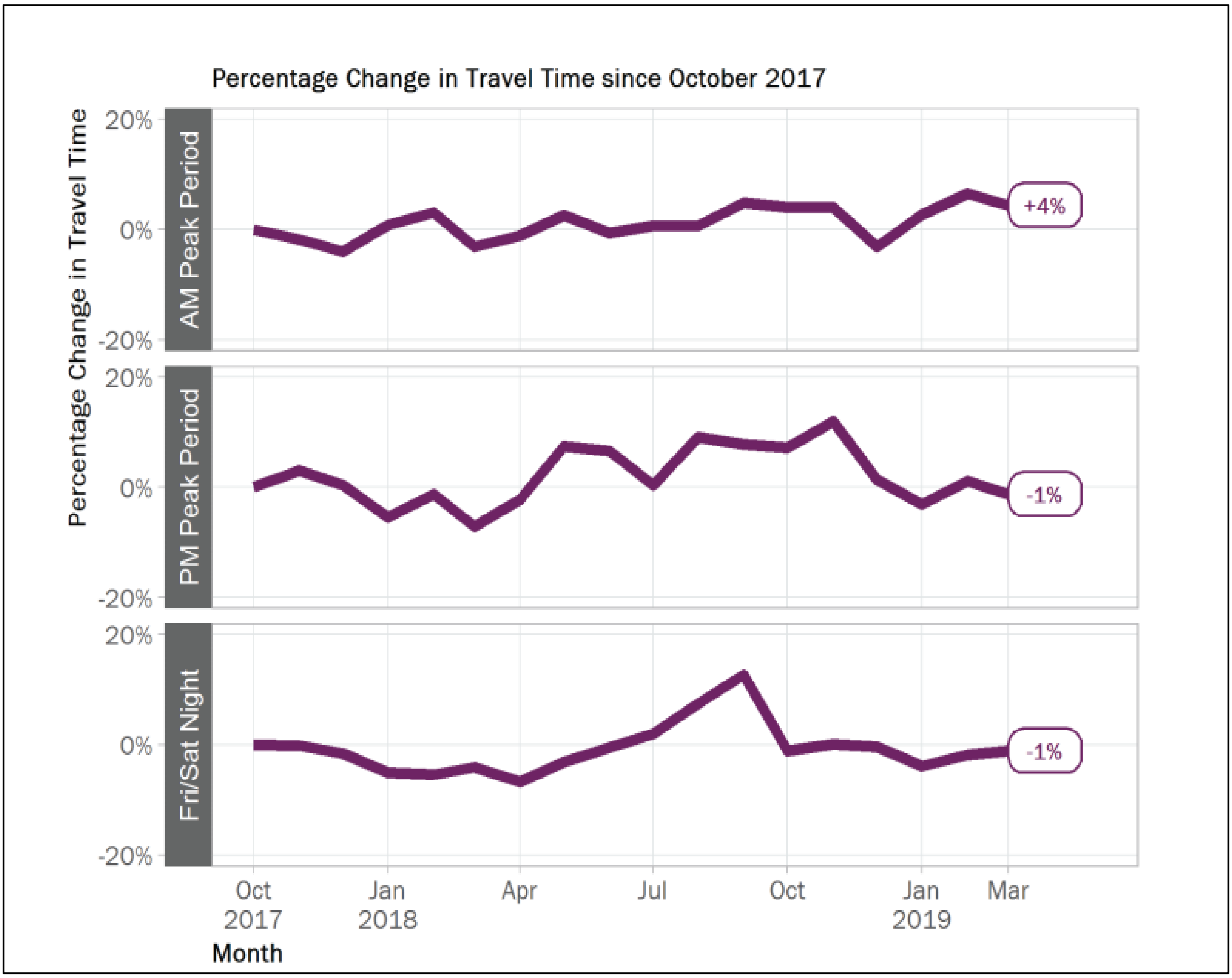

Fig 5 Monthly average travel time in Toronto's downtown core for the a.m. and p.m. commute periods, and for Friday/Saturday night. Times are normalized to their October 2017 averages to highlight fractional changes.

- *Downtown Travel Times have been Stable over 18 Months while Ridesourcing Trips Increased by 96%*

Figure 5 shows the percent change in normal travel time in view of Bluetooth sensor readings on most significant roads in the midtown center, the region of the City where it are most noteworthy to ridesourcing trip fixations. This information shows minimal changes in movement times over the year and a half from October 2017 to Walk 2019 in the midtown center. Travel times on significant roads have expanded by 4% in the first part of the day top hour (7 to 10 a.m.), and diminished by 1% in both the midday top period (4 to 7 p.m.) and Friday and Saturday evenings (10 p.m. to 1 a.m.). Over this equivalent range, ridesourcing trips expanded 96% extensive, from 83,800 to 164,000 day to day trips.

Considering that adjustments of movement times have been unimportant in the areas where ridesourcing makes up the biggest extents of generally speaking traffic, there is lacking proof right now to make any authoritative linkages between ridesourcing volumes and changes in movement time.

- *Pick-up and drop-off Data Highlight Conflicts with no-Stopping Zones and Bike Lanes*

A specific wellbeing worry with ridesourcing get and dropoff action is likely struggles with cyclists, particularly when it happens in closeness to cycling foundation. A point by point take a gander at get/drop-off information has shown areas of interest during the morning drive period where get and drop-off action is happening in no-halting zones. The biggest areas of interest are in the Monetary Locale. Figure 6 shows a comparative investigation of pick-ups and drop-offs nearby bicycle paths and isolated bicycle offices between 7 a.m. also, 7 p.m. during a run of the mill work day in September 2018. There is a huge volume of get and drop-off action close to high-utilize bicycle offices. This features areas that could profit from extra partition between bicycle paths and vehicular traffic. Regardless of the more noteworthy exactness of the positions, it is difficult to finish up from this information whether the ridesourcing vehicle was inside or contiguous a bicycle path while getting or dropping off travelers. By and by, these areas of interest show where they might be a highgamble of clashes.

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V. DISCUSSION

This section presents the results and outcomes of this study in context with other regulatory analyses.

➢ *Congestion*

A comparison of ridesourcing VMT as a proportion of total VMT with other cities that have performed similar studies shows that Toronto is at an earlier stage of maturity. The TNCs Today report by the SFCTA estimated VMT from ridesourcing vehicles to be at 6.5% of city-wide weekday VMT [?] in 2016. A 2019 report by the NYC Taxi and Limousine Commission and the NYC Department of Transportation estimates 30% of VMT in Manhattan can be attributed to ridesourcing vehicles [6]. The same report recommends continuing the freeze on issuing new licenses to ridesourcing drivers and requiring ridesourcing companies to reduce cruising (any time spend with the ridesourcing app on but without passengers) as a percentage of driving time to 31% in Manhattan.

➢ *Curbside Management*

A number of cities have implement dedicated passenger loading/unloading zones to respond to growing demand for curb space, to reduce conflicts with competing uses for curb access, and as part of their Vision Zero programs. These include [?] and Washington, D.C.. The City of Toronto will use pick-up/drop-off (PUDO) data to inform the design of bike infrastructure and inform prioritization of infrastructure upgrades. Further study would be expected to decide how assigned traveler stacking zones could be carried out and how giving digitized check guideline information could better oversee control usage. Extra checking and examination is expected to better comprehend the degree of contentions among cyclists and get and drop-off action and to decide whether this movement associates with gotten to the next level cycling solace and diminished paces of cyclist clashes.

VI. CONCLUSION

This study has seen what is doubtlessly the principal wave of interruptions from new versatility organizations in Toronto. Trip development isn't expected to slow in the impending years and these administrations will probably make traffic and functional difficulties all through the City later on. Nonetheless, the quick development in trips exhibits ridesourcing administrations have been hugely famous with Toronto occupants. They presently assume a significant part in many occupants' everyday travel designs remembering a rising job for day to day suburbanite travel.

A chief rundown of the Transportation Effects of Vehicle for- Recruit report was connected to the Staff Report ready by Metropolitan Authorizing & Principles and introduced to the Overall Administration & Authorizing panel on June 24, 2019. Councilors mentioned we report on the quantity of rideobtaining vehicles working and to expound on our discoveries in regards to blockage. The report and these extra examinations were talked about at City Board on July eighteenth. Council approved staff recommendations, with amendments. The following relevant regulations were approved:

- Request that taxi/ridesourcing be a field on the standardized collision reporting form. Require that all vehicle for hire brokerages and companies report collision incidents.
- Create an accessibility fund to encourage the purchases of accessible vehicles.
- Require that all vehicle for hire drivers receive driver training.
- Require additional data to be provide by ridesourcing companies: aggregate vehicle volumes in geographic areas, pick-up and drop-off data at a 10m resolution, aggregate number of vehicles having completed trips by hour.
- Require that taxi brokerages provide similar trip record data as ridesourcing companies

Council further required Transportation Services to report in 2020 on whether there has been an impact on congestion from vehicles for hire, what mitigating measures can be taken, and determine the appropriate number of vehicles for hire. Council also required a report on the safety of ridesourcing operations and the feasibility of requiring vehicle for hire applications to route them such that they do not stop to pick-up or drop-off passengers in "no stopping" zones.

The objective of the Transportation Effect Study was to construct a more profound comprehension of these new administrations and to make ready for future work and studies to keep before these quickly evolving patterns. This will permit the City to characterize strategy to help the advantages of ridesourcing administrations while limiting unfavorable effects on traffic, to the climate and to the value of portability administrations. Having performed this comprehensive study, we claim that transportation agencies need three important datasets to be derived from ridesourcing activity, each which its own utility for regulation:

- **Trip OD records:** for transportation planning;

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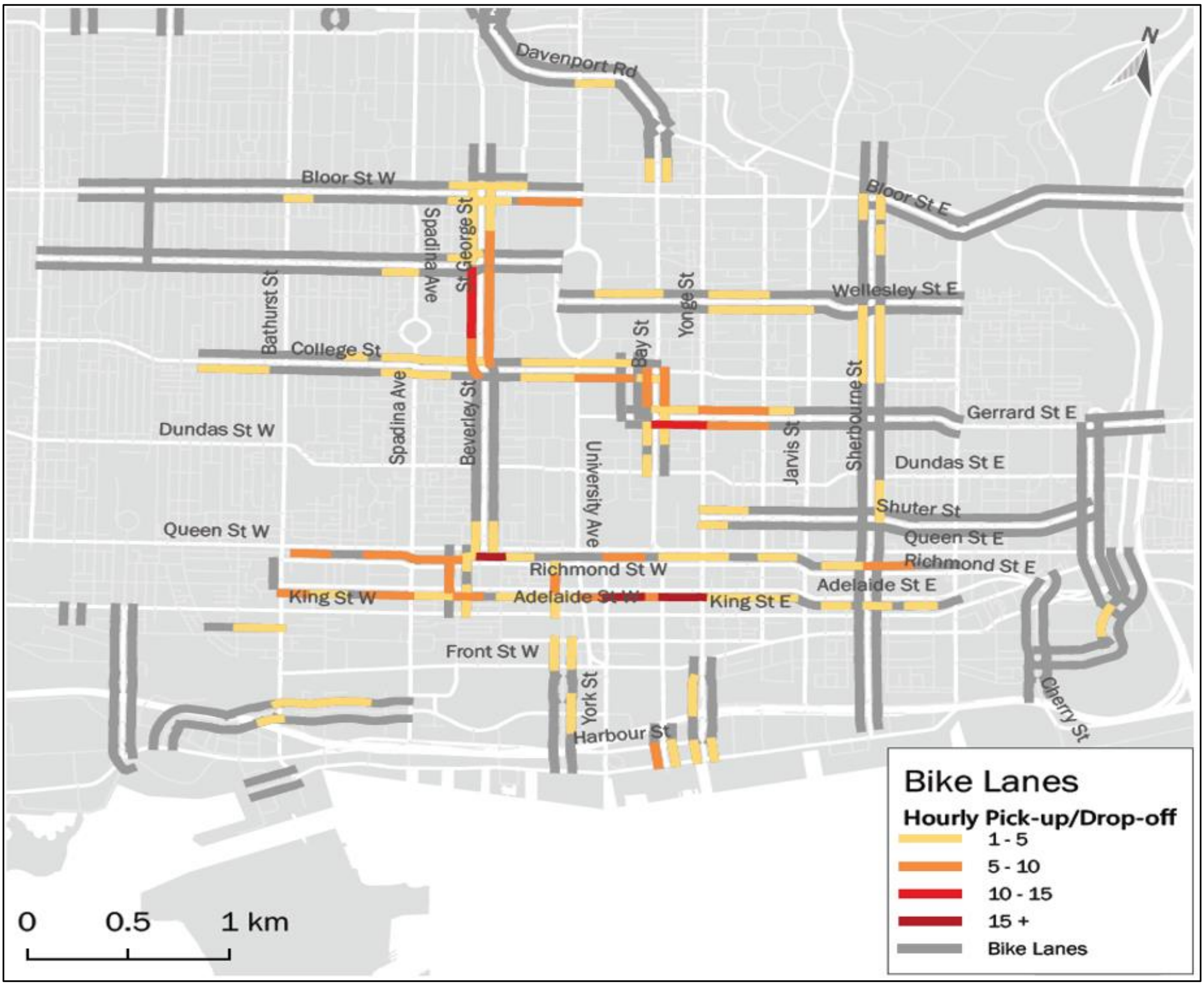

Fig 6 Hourly average number of ridesourcing pick-ups and drop-offs adjacent to bike lanes and separated bike facilities between 7 a.m. and 7 p.m. Data is averaged from Monday, September 10 to Thursday, September 13, 2018.

- **Ridesourcing vehicle volumes**: for congestion management; and
- **Pick-up/drop-off activity:** for curbside management and vision zero planning.

For the purposes of this study we were provided trip records and PUDO data, and we presented a novel process to derive vehicle volumes from trip records which other agencies could use.

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