

Analysis of TNC passenger and driver responses to curb-space allocation
in urban land use contexts

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Abstract

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In response to the growing recognition of impacts from TNC vehicles, some major American municipalities are considering or have implemented regulatory practices intended to promote public curb space allocation in line with long-term planning goals of safety and environmental sustainability. Some of the proposed regulatory policies center the reallocation of a significant amount of public right-of-way for the use and benefit of private TNC vehicle operations. This thesis project proposes both: a conceptual computer model, built using the agent-based program NetLogo, of the trade-offs which reallocation of curb space can affect; and a matrix, informed by observation of trade-offs in the model, with which decision-makers can evaluate options for policy intervention in a variety of urban land use contexts. The study applies the model and matrix to two interventions proposed by the transportation consultancy Fehr & Peers.

(1) Introduction

This introduction provides: **(i)** a pocket history of the development of the TNC market; **(ii)** an overview of the policy need to which this thesis responds; **(iii)** an outline of the rest of the paper.

(i) Summary history of the TNC market

The first companies regulated as “transportation network companies”, or TNCs, began operation in San Francisco, California in 2011/2012. Both of the initial market entrants — Sidecar and Lyft — were an evolution of prior businesses that provided for-hire transportation through privately owned fleets. These businesses were constrained by the high capital cost of expanding their “ridesharing” operations, which required paying for additional vehicles as well as their storage and maintenance. But the widespread adoption of personal smartphones with GPS-based location tracking capability allowed the new TNC businesses (at the time still referring to their operations as “ridesharing” services) to integrate an individual’s personal vehicle into the service network. This shifted the capital cost of expanding service off of the TNC businesses and onto their employees, lowering the cost to TNCs of expanding service capacity rapidly with demand. The new services responded to the lower cost of expansion by hiring drivers without requiring the background checks, permits or insurance legally required by local and state agencies (Flores & Rayle).

While these initial entrants, and the latecomer UberX, avoided regulatory attention for their first year of operation, pressure for regulation grew as demand increased and TNCs became more visible to regulators and the existing taxi industry. While San Francisco Mayor Ed Lee acted to shield them from local regulation, TNC businesses began recruiting drivers and passengers for advocacy efforts to protect and formalize their businesses as a new private transportation market. In 2013, acting in part on the private urging of Mayor Lee, the California Public Utilities Commission adopted a new state-wide regulatory framework for TNC operations. The new framework adopted a light regulatory touch in an effort to protect and promote the TNC industry (Flores & Rayle).

Subsequent initial regulation (at the local and state levels) of the TNC sector in most American jurisdictions adopted this light-touch approach (Flores & Rayle). However, in the past two years or so public awareness of the external costs of TNC operations has increased. A series of high-profile suicides by taxi medallion owners in New York City drew attention to the significant reduction in private driver incomes which has followed mass adoption of TNC services (Bellafonte). In Seattle, Washington a 2018 report by Schaller Consulting that TNC vehicles added “94 million” vehicle miles traveled (VMT) to city streets in 2017 received significant local coverage (e.g., Adolph). After initially backing off a similar plan in 2015, the New York City government recently acted to cap the total number of for-hire vehicles legally operable in the city, with the express purpose of curbing both of the above-stated externalities (Fitzsimmons). The Seattle Mayor’s Office reportedly prepared a draft policy for additional per-trip

fees on TNC operations in the past year (Beekman). This thesis is therefore positioned in the context of a (re-)emerging willingness among municipal governments to intervene in the urban transportation market.

There are several clear policy axes along which municipal intervention might occur, e.g.: the price of the service, as with trip fees reportedly being considered in Seattle; the allowable market supply, as under New York City's vehicle cap; labour conditions, as in City of Seattle legislation requiring TNC drivers be allowed to unionize; minimum service requirements, as in a minimum vehicle emissions profile or ADA compliance; and pick-up / drop-off, or curb-space, behaviour.

I have chosen to focus on curb-space behaviour for two reasons. First, although there are several robust investigations of TNC impacts on urban VMT and traffic congestion in recent literature (e.g., Henao & Marshall; Schaller), I have not found a body of modeling for TNC behaviour at the block-face level.¹ As TNC services have generally been unwilling to share block-level data with municipal governments, this absence is likely due to the increasing level of specificity in data required when one is modeling *impacts* at increasingly precise geographic scales. And second, although modeling impacts (e.g., on intersection level-of-service) at the block-face level requires a great deal of specificity in data collection, developing an agent-based model of trade-offs between policy *concepts* at the same scale does not require access to data at the same specificity.

¹ Goodchild & MacKenzie at the University of Washington Urban Freight Lab are currently preparing a report on observed block-level behaviour for the Seattle Dept. of Transportation (SDOT).

(ii) Curb-space policy

Concomitant with the growth of the TNC mode has been an increase in demands for curb-space to facilitate vehicle boarding and alighting. At the same time, my literature review confirms what casual observation of the mode would suggest: TNC passengers or drivers can and often will elect to perform boarding and alighting in the active roadway, instead of at the curb. Both these consequences of modal growth can have significant impacts on the safety and efficiency of roadway operations. Increased demand for curb-space use increases competition for curb-space, puts pressure on parking availability, and can push commercial freight and passenger loading operations into the active roadway. TNC passenger loading in an active roadway increases the potential for vehicle-pedestrian and vehicle-vehicle collisions; it can equally impede private traffic and public transit vehicles. In 2018, transportation consultants Fehr & Peers prepared a study of curb-space allocation on several block-faces in San Francisco for Uber Technologies. Fehr & Peers aimed to propose policy interventions that might more efficiently allocate existing curb-space while reducing impacts from in-roadway TNC loading operations. Their study developed a metric for evaluating allocation of curb-space (passengers served / time per linear foot of curb space), as well as 3 species of curb-space policy interventions responding to the land-use contexts studied. These interventions frame the research question for the current thesis project. A hypothetical block-face was simulated in the agent-based model as an “existing”, control, scenario. Two of the interventions

proposed by Fehr & Peers were then used to develop simulations of intervention on the “existing” block-face. The results generated were used to inform an evaluation based on the evaluation matrix developed for the thesis.

(iii) Outline of the paper

Chapter (2) below describes the literature reviewed to develop the current regulatory context of TNC services, the policy issues occurring around current curb-space allocation, and the modeling approach by which interventions were evaluated. Chapter (3) then outlines the logic model used to drive behaviour of the agents in the model, as well as the conceptual model of policy impacts resulting from TNC curb-space behaviour and the policy matrix used to evaluate those impacts. Chapter (4) details the different curb-space allocation scenarios observed through our agent-based model, with two scenarios implementing an intervention based on Fehr & Peers’ proposed options. Chapter (5) then details the evaluations produced by applying our matrix to the results observed in each modeled scenario. Chapter (6) concludes with a discussion of methodological limitations and of the directions in which it could be profitably extended.

(2) Literature review

This literature review covers: **(i)** a survey of transportation professionals on the regulatory future surrounding TNCs; **(ii)** the policy need to which this paper responds; **(iii)** the set of policy goals, adapted from City of Seattle Comprehensive Plan goals, used to evaluate potential interventions; **(iv)** the set of policy options for curb-space allocation proposed by the transportation consultancy Fehr & Peers; and **(v)** the agent-based modeling approach adopted to inform the evaluation.

2.1 - Directions for future regulatory regimes

Any comprehensive revision of the regulatory framework for curb space allocation will occur with reference to larger trends in transportation modal demand and policy. A paper by Aarhaug & Olsen collecting predictions of individual trends in urban transportation economies into three aggregated scenarios was therefore reviewed in order to place the current study in the context of potential large-scale changes to the transportation environment. A summary of findings follows.

Aarhaug & Olsen surveyed experts in the fields of transportation planning and economics for their predictions of likely outcomes in the transportation sector. (Individual outcomes were, e.g., “The sharing economy flopped and does not affect travel mode choice”; “Self-driving vehicles have replaced the traditional car”; etc.). These individual outcomes were then grouped by their propensity to be predicted together. The groupings generated three scenarios for 2030:

1. The “business as usual” scenario, wherein a decreased percentage of vehicle ownership in urban areas is offset by the level of urban population growth to produce an overall increase in the number of cars. In this scenario, demand on mobility-as-a-service (MaaS) platforms increases, but vehicles remain human-operated. The low-income population expands.
2. The “conservative” scenario, wherein the cost for TNC services charged on MaaS platforms increases in tandem with, but at a higher rate than, the cost of private vehicle ownership. This scenario envisions continuing reductions in urban affordability, increases in congestion, and a political environment that subsidizes private vehicle ownership over other modes.
3. The “technology” scenario, wherein economic polarization (reduction of the middle class) increases due to the wealthy’s ability to capture an increasing proportion of the economic benefits of automation. This scenario sees an increase in adoption of MaaS platforms as TNC operations hybridize with traditional public transit modes (e.g., a quasi-public monopoly TNC service integrates its offerings with a public-private MaaS platform).

In the “business as usual” scenario, urban centers would expect to see an increase in TNC volume from current levels. Because (in this scenario) the

increased service volume is not accompanied by a transition to autonomous TNC vehicles, scenario 1 would not eliminate the modal behaviour that produces our policy need without further intervention. The TNC mode would still put pressure on other existing curbspace uses, and the continued presence of human drivers would mean TNC loading behaviour was still open to the discretion of individual drivers and passengers. With increasing demand and no corresponding introduction of a comprehensive management system for the mode, it seems likely that in-roadway loading behaviour would remain as, or become more, prevalent. “Business-as-usual” is therefore the scenario most likely to produce block-level interventions by urban municipalities to adjust existing curbspace regulation.

Scenario 2 partially resolves the curbspace question (for TNCs) due to the projected predominance of private vehicle ownership. The continued public subsidy for private vehicle ownership and the increasing costs for TNC services suggest demand for TNCs under this scenario would be expected to shrink. The extent of curbspace allocation that cities would have to adjust is thus the smallest in scenario 2. The policy interventions proposed by Fehr & Peers, and evaluated in this thesis, would likely not occur outside of land-use contexts that occasioned high concentrations of TNC modal demand (e.g., large sporting arenas).

In scenario 3, the increased automation of TNC operations may allow for a neighbourhood- or city-wide policy of dynamic curbspace use and allocation. As technology advances, decreasing marginal costs for TNC rides may increase

modal demand, requiring a more comprehensive curb-space allocation policy. Equally, economic polarization may reduce overall TNC modal demand, and/or marginal willingness to pay, below profitability, thereby dramatically shrinking TNC mode share. Given the level of uncertainty currently associated with autonomous vehicles, it would be unwise to treat this scenario further in a master's thesis project.

Because, therefore, it incorporates the highest need for the type of policy interventions we are evaluating (without introducing an unmanageable complexity), this thesis project was designed in view of the context of scenario 1 — “business as usual”. Policy interventions were modeled and evaluated with the expectations that: both private vehicle and TNC vehicle demand will increase; that virtually all vehicles will continue to be human-operated; and that the (dis-)incentives TNC passengers and drivers face between in-roadway and at-curb loading will remain structurally similar to those existing today. The understanding of these incentives which was developed for this thesis, and of the impacts in-street loading can occasion, are now outlined in section 2.2.

2.2 - Current TNC loading behaviour and its immediate impacts

TNC drivers face economic and platform incentives to ensure customer satisfaction with rides and to minimize time spent in operation without a fare. (Heno & Marshall) As a part of meeting both of these incentives, drivers may

seek to optimize passenger boarding and alighting by minimizing vehicle time spent pulling into, idling at, and pulling out of the segment of right-of-way being used for pick-up or drop-off section. Once in the vehicle, passengers may encourage and / or direct this optimization behaviour by indicating their own preferred drop-off location to the driver. They may also offer additional incentives (e.g., a larger tip or a 5-star driver rating) in exchange for a driver meeting a specific drop-off request. (*FEIS*)

From a safety perspective, the ideal segment of the right-of-way for passenger pick-up and drop-off is typically the curbside “flex zone” (sometimes referred to as a parking lane). (Fehr & Peers) However, in a dense urban land use context such as downtown commercial core, night-life district, or special-event arena district, competition for curb space can be severe. (Xu et. al.) A driver may be unable to access a loading zone on the passenger’s preferred street segment. In these circumstances, drivers may elect (either of their own volition or per a passenger’s request) to allow a passenger to board / alight in the travel lane. (Fehr & Peers)

Beyond the immediate safety impact to the passenger of alighting a vehicle while still in the travel lane, TNC pick-up and drop-off in areas with heavy competition for curb space may have impacts to traffic flow and to the safety of other modes. Traffic flow can be blocked by vehicles stopped in the travel lane or attempting to enter / exit a small width of curb space. (Fehr & Peers) Blocked vehicles may undertake unsafe contra-flow maneuvers in order to bypass an idling TNC. Bicycle and transit-priority lanes can also be blocked by TNC

vehicles that are unable or unwilling to access available curb space on other street segments. (*FEIS*) Private vehicles may be unable to locate parking efficiently. The likelihood of these impacts may then be aggravated by a failure to comply with designated curb space allocation — a passenger may (for example) elect to alight in a travel lane because it is closer to their final destination than the designated load / unload curb-space. The dispersed nature of the TNC mode and the relatively short time frame required for boarding and (especially) alighting can make it quite difficult to enforce the designated uses of curb space and curb-side lanes, even when TNC vehicles are present at scale in a confined area. (*AAMP*)

This thesis project responds to the impacts occasioned by the platform and economic incentives described above from the literature; it does not address interventions that might affect those incentives themselves (e.g., eliminating driver ratings from a TNC platform). That scope removes any need for our model to incorporate parameters defining an agent's beliefs and intentions toward platform or economic incentives. What remains are the impacts themselves; the rate at which they occur; and the changes in behaviour introduced by whatever regime is in place for the allocation of curb-space (e.g., the availability of reserved passenger load-zones v. private parking). For this project, the following quantified impacts were selected from the set outlined above: **(i)** vehicles unable to access a parking space / load zone; **(ii)** the rate and number of loading operations occurring in the roadway; **(iii)** unsafe vehicle

passing maneuvers (passing both pedestrians and other vehicles); and **(iv)** the amount of time, aggregated across individual vehicles, of observed vehicle queuing / idling.

In the following sections of the literature review, I outline the policy interventions modeled (2.3) and the criteria used to evaluate them (2.4). An in-depth discussion of the types of impacts observed through agent-based modeling is found in section 3.3; changes in behaviour observed after each intervention are discussed in chapter (4).

2.3 - Policy interventions

As we have said, the policy options for allocating curb-space in response to TNC operations evaluated in this thesis were developed from a 2018 report by the transportation consultancy Fehr & Peers. The firm monitored curb space usage, traffic flow and modal conflicts in several land use contexts in San Francisco, together with data provided by Uber Technologies summarizing the TNC service's demand volume in these contexts. The contexts evaluated included: downtown office core; a "transportation hub" (i.e., transfer center with heavy volume on and transfers between rail, bus, private vehicle and TNC modes); a neighbourhood shopping and dining district; and a corridor with significant bicycle traffic.

To guide their analysis, Fehr & Peers developed a conceptual index of "curb space productivity". This index evaluates the designation of a segment of curb

space / flex zone under the rubric of the number of passenger load / unload events that occur per linear foot per hour. Modes (like private vehicle parking) that turn over slowly would be expected to have a lower average curb space productivity than modes (like public transit) that turn over quickly and / or serve higher volumes of passengers simultaneously. By comparing the extent of curb space assigned to each mode against their relative productivity, the model aims to identify “inefficient” allocations of curb space on street segments where observation indicates significant competition for it.

It should be considered, however, that this “curb space productivity” metric arguably describes a kind of “curb-space level-of-service” (LoS) experienced by TNC passengers. The more curb-space allocated to providing a quick, efficient and safe passenger pick-up / drop-off, the higher will be the passenger’s experience of the LoS. This will have implications for our policy evaluation, as described in the following section 2.4; but we describe each intervention first.

Once a street segment is identified as having inefficient curb space allocation, Fehr & Peers propose three policy options for reallocation of the flex zone. The options are:

1. Relocation — this would be the relocation of a designated load / unload zone from one street segment to another. The underlying idea is that load zones adjacent to each other or to curb allocations with which they would not be expected to regularly compete (e.g., driveways) can be more productive for high-turnover uses like TNCs than when they are

adjacent to private vehicle parking. The increase in productivity is due to the enhanced speed with which a vehicle can enter and exit the load zone when there are no fixed objects which the TNC driver must avoid in the adjacent flex zone segment. *This intervention was not modeled, as it relies on a logical construct — ease of turning maneuvers — which is not reflected in the logic model developed for our ABM.*

2. Conversion — this idea is straightforward, although it may have significant policy or equity impacts. After an evaluation of the productivity of existing curb space allocation finds that too much of the flex zone has been assigned to modes with low curb space productivity (e.g., private parking), space is reassigned from less to more efficient modes. Policy and equity impacts arise both because removal of parking does not inherently reduce parking demand (Xu et. al.), and because the curb-space productivity metric returns evaluations that reflect pre-existing demand patterns. An in-street bicycle parking rack (for instance) may not serve a high demand, but this could only reflect a lack of nearby bike infrastructure. Removal of the rack may push bicycle volumes lower due to an increased lack of infrastructure while pushing demand for other modes, like TNC services, higher. *This intervention was modeled.*

3. Flexibility — As proposed by Fehr & Peers, this indicates the conversion of an existing load / unload zone reserved for a single mode into a shared load zone accommodating multiple modes, with the designated use changing over the course of the day. The firm envisioned

the use of dynamic signage, demand monitoring, and / or geofencing to allow flexible allocation over the course of the day. *A version of this intervention was modeled*, but, the model was not intended to reflect conditions over the course of a full day. Only AM- and PM-commute peak conditions are simulated. This precludes an evaluation of a direct implementation of Fehr & Peers' "flexibility" intervention, but it does not prevent us from modeling the concept of multiple modes competing to use the same curb space. The "flexibility" intervention as evaluated in this study implements this concept.

The modeled interventions thus share an element of trading off allocation of curb-space between private parking and passenger load-zones. To evaluate the interventions requires understanding the consequences of these trade-offs and criteria by which to judge them. Criteria are developed in the below section 2.4, and the agent-based modeling approach used to identify the consequences of intervention in section 2.5. The specific parameters of the control and intervention scenarios used in modeling are described in chapter (4).

2.4 - Policy evaluation

This thesis project aims to evaluate the curb-space allocation interventions proposed by Fehr & Peers by modeling their effect on a subset of the impacts outlined in section 2.2. To guide the evaluation of impacts, I reviewed the general

goals and subsidiary policies outlined in the 2019 Amended City of Seattle Comprehensive Plan’s Transportation section (hereafter *CoS 2035*). Each criterion is numbered in this section like so: **(n)**.

A part of the relevant regulatory context in *CoS 2035* is found in policy **T 3.8**: “Work with transportation providers, such as car share, bike share and taxi providers, to provide access to their services throughout the city and to maintain the affordability of their services”. This is echoed and developed in **T 3.16**:

Support and plan for innovation in transportation options and shared mobility, including car sharing, bike sharing, and transportation network companies, that can increase travel options, enhance mobility, and provide first- and last-mile connections for people.

The curb-space allocation interventions Fehr & Peers propose are intended to enhance the safety and reliability of access to the services which TNCs provide.² *CoS 2035* should therefore be read as expressing a willingness in principle to implement interventions like those we are evaluating. The assertion that TNCs can “increase travel options” and “provide first- and last-mile connections” identifies the general transportation functions which it is City policy to support TNCs in fulfilling.

More specific criteria for the desirability of intervention in curb-space allocation are laid out in other policies. **T 3.18** recommends “curb-space management strategies” that “promote transportation choices, encourage parking turnover, improve customer access, and provide for efficient allocation

² Detail on each intervention is found above, in section 2.3.

of parking among diverse users”. This suggests that the City would view positively an intervention that: **(i)** increased the number of drop-offs on a block-face in a retail district (“customer access”), or **(ii)** decreased the number of in-street drop-offs on a block-face where current curb-space allocation conflicts with efficiently serving the predominant modal activity (e.g., if the curb adjacent to an office building was allocated exclusively for all-day public-parking). **T 3.18** also supports the “curb space productivity” criterion developed by Fehr & Peers (passengers served per linear foot per hour).

But several *CoS 2035* policies propose criteria that could weigh against interventions like those proposed by Fehr & Peers. **T 2.3** is representative: “Consider safety concerns, modal master plans, and adjacent land uses when prioritizing functions in the pedestrian, travel way, and flex zones of the right-of-way.” Safety is, as here, the primary evaluative criterion for intervention in the right-of-way across multiple *CoS 2035* goals and subsidiary policies (e.g., goal **TG 2**; **T 2.5**). Modal plan functions (e.g., **T 2.2**; **T 2.5**; **T 3.4**) and appropriateness to existing and planned land-uses (e.g., **T 2.7**) are likewise noted throughout *CoS 2035*.

CoS 2035 transportation policy will therefore judge intervention: **(iii)** positively if modeling shows it may decrease the potential for conflicts, and harshly if modeling should show the reverse. But the latter two criteria — modal plan function and land-use context — complicate this evaluation. They introduce the consideration that in a “fully-built city” like Seattle, allocation of right-of-way to any one modal use may likely necessitate denying its use by another mode.

The more obvious example may be competition for roadway between bus- or bike-only lanes and vehicular traffic, but the idea equally applies to curbspace allocation, and this latter both directly and indirectly. Directly, in that adding passenger load-zones often means removing public parking; indirectly, in that adding infrastructure for one mode (e.g., parking for private vehicles) increases that mode's desirability relative to other modes. A policy evaluation based on *CoS 2035* would therefore judge intervention in curbspace allocation negatively: **(iv)** to the extent that it directly conflicts with the land-use context or plans for modal infrastructure; and **(v)** if it unduly raises the competitiveness of one mode where modal planning had intended the priority of another.

What is required for our evaluation, then, is not only to balance positive outcomes *CoS 2035* countenances (first- and last-mile connections; more efficient use of curbspace) against the negative impacts occasioned by TNC curbspace behaviour. To the extent that the proposed policy interventions may reduce these negative impacts and align with land-use goals, our evaluation must still weigh those benefits against policy goals supporting other modes. Intervention should not preclude access for a diverse set of modes or conflict with city-wide modal plans, including policies to promote walking and biking (**T 3.14**).

The relationship between land-use context and the modal choices policymakers may wish to promote is evaluated qualitatively in chapter (5) using

the *Cos 2035* policies we have discussed here.³ But these considerations should also help develop the point, made in section 2.3 above, that the “curb space productivity” index developed by Fehr & Peers can equally be taken as a measure of LoS for TNC loading operations.

Our claim before was that, as the safety and efficiency of TNC loading increases, passenger satisfaction with the service may likewise increase. All things being equal, this would be expected to promote TNC services’ mode share. We can likewise develop from the literature negative impacts of intervention on the desirability of other modes. A 2018 report from Schaller Consulting summarizing three stated-preference studies states: “only a few percentage of auto users choose TNCs due to convenience or speed of travel”. Instead, and across each study, auto users choosing TNC services report “parking is difficult, “expensive” or “difficult to find” as a top three element in their modal choice. In our policy context (i.e., a “fully-built city” like Seattle), it should be understood that increasing the effective LoS for TNC loading by reassigning curb-space from public parking to passenger load-zones will most likely reduce the supply of public parking and thereby make it more difficult to find and access. Likewise, two of the studies cited by Schaller found that the first reasons individuals select for opting for a TNC service over public transit “involve these core attributes: transit too slow, unavailable or unreliable”. It has already been established that TNC loading operations can delay transit service

³ See section 3.4 below for the full policy evaluation matrix.

when TNC vehicles or passengers block the roadway (*FEIS; AAMP*). It is therefore reasonable to conclude that some of the impacts of the TNC loading operations which we are modeling can have a negative impact on transit mode share.

Capturing the quantitative extent of these mode share and performance impacts is beyond the scope of this project. However, the agent-based modeling approach adopted to inform our evaluation can provide a robust conceptual understanding of direct impacts from TNC curbspace behaviour; this understanding can in turn support or cast doubt on the relationships to safety and modal desirability we have described. Any inferences about modal desirability, together with conceptual conclusions derived from the more direct impacts of loading behaviour observed in the model, are what we will use to evaluate each intervention under the policy criteria here developed. The literature review therefore concludes with a study of agent-based modeling, both in general and in the field of transportation.

2.5 - Modeling

This section provides **(i)** an overview of the concept and value of our operative research method, the “agent-based model”; **(ii)** an explanation of the processes and truth-status for verification and validation of an agent-based model; **(iii)** a review of the literature which guided the specification of our model.

2.5.1 - The concept of agent-based modeling⁴

“Agent-based model” (ABM) refers to a computer model of a research phenomenon generated through the specification of actions which “agents”, understood as constituting the granular level of the research phenomenon, can take in a determined environment.⁵ Unlike a regression model, an ABM is not necessarily intended to estimate correlations between experimental factors and an outcome. Instead, an ABM externalizes a consistent representation of a pre-determined logic model of the individual agents’ behaviour. This allows the researcher to (i) observe the system which the logic model in fact generates when it is consistently enacted by agents in a specified environment. As the individual agents are taken as constituting the granular level of the research phenomenon, the systematic externalization of their simultaneous action is in turn taken as an externalized conceptual representation of the research phenomenon itself. The well-known “NetLogo Traffic Basic” model (Wilensky 1998), for instance, shows how traffic congestion can emerge under a logic model of driving behaviour as simple as that individual drivers will accelerate and decelerate within bands of average speeds in order to maintain a specific desired speed and minimum distance from other vehicles.

Once a logic model for agents’ actions has been specified and the resulting

⁴ Both this section and 2.5.2 draw from Wilensky & Rand’s excellent *An Introduction to Agent-Based Modeling* (2015) and conversations with Prof Marina Alberti.

⁵ This does not mean an “agent” must be a person, or even a non-corporate entity. The specificity of the agent in an ABM is determined by the level of analysis: if one is modeling land-use outcomes at the block level, the agents may be individual property owners; at the regional level, the “agents” may be governments, large development firms, etc.

system observed, ABM also allows the researcher to **(ii)** observe changes in the behaviour of individual agents, and in the overall system, as a specific element of the logic model or a specific property of the environment varies. So, returning to the “Traffic Basic” model, the researcher can vary the number of cars on the road; or the minimum distance from other vehicles they will tolerate before slowing; or their maximum allowable desired speed; or the quality of the road surface; or all of these factors together; in order to observe how the given change affects the propensity of the logic model, applied at the agent level, to generate outcomes (like traffic congestion) at the system level. This is invaluable to the researcher as a means of observing trade-offs between the operative concepts in the logic model — and, in principle, the research phenomenon.⁶

Building an ABM thus means specifying: the properties of the environment in which agents act; the properties for which each class of agent is capable of reporting a state; and the criteria for reported states of properties under which the logic model directs an agent to take each possible agent action. This last set of parameters, relating agent-states to directives for action, are the “micro-level rules” of the model (e.g., if the agent is on a blue patch, the agent moves forward 1 distance unit). The ABM “sets up” by placing agents in the environment as directed and determining the initial state of their relevant properties, then applies the relevant micro-level rules to each agent in a sequence determined by the researcher. This advances the state of the system: each rule directs agents that

⁶ Detail on the process and requirements for confirming relevance between the ABM and the “real” research phenomenon can be found below, in section 2.4.2.

report property-states (i.e., the colour of the agent's current patch) matching the criteria of the rule to take a specific action. Once the system has applied each rule to all relevant agents and each agent has taken the appropriate (in)action, the ABM repeats the query-action cycle.⁷ By this process of chaining together individual micro-level actions, a complex action like walking around a city block can be generated. The properties of an agent and the micro-level actions of which they are capable can be as simple as a binary state (e.g., red : blue :: on : off), or quite complex.

A second consideration generated by my review of ABM literature and conversation with research practitioners needs raising here.

The research value of an ABM is not primarily produced by the closeness of its fit to real-world observations of the research phenomenon in a given context. It is thus not necessary, and can quickly become counter-productive, to minutely determine the logic model underlying the behaviour of the modeled agents in order to produce behaviour in the ABM that precisely mirrors the research phenomenon as it naturally occurs. Again, this is because the aim of ABM research is not necessarily to predict the likelihood of specific outcomes. ABM research aims rather to observe the (inter-)actions produced by rigorous application of the researcher's own considered understanding of the actions individual agents take. This allows for positive inferences about the relationship

⁷ Note that this introduces a time-unit into the ABM, measured by the number of times the ABM "turns over", or repeats the query-action process. In the NetLogo software used for this thesis, these time-units are called "ticks".

of concepts in the logic model to the research phenomenon. But, and potentially equally valuable, it also allows for a negative determination: that what appeared to be a plausible logic model for agent behaviour in the research phenomenon does not in fact produce the emergent patterns observed in the “real” world.

A researcher may, therefore, design an ABM with the expectation that it will produce a representation of a specific emergent phenomenon (like traffic congestion). But the ABM is not worthless from a research perspective if the logic model fails to generate the emergent phenomenon the researcher expected. It is more important that the logic model for individual behaviour underlying the ABM reflect the researcher’s understanding of the agents’ actions. The logic model should therefore direct each agent’s action independently, without itself referring to the systemic phenomena which their behaviour collectively produces.

In practice, this means: **(a)** the logic model’s criteria for when the ABM directs an agent to take any given action should be construed as generically as possible; and **(b)**, that agents should not be denied (or provided) relevant information by the logic model that they would (not) be able to independently observe in the “real” world. The latter concern is fairly straightforward — pedestrian agents in an ABM of crosswalk behaviour should not, for instance, be “told” by the ABM that a vehicle is speeding towards them if the underlying logic model would not allow them to observe this independently. Application of **(a)** can be less clear-cut, but the idea of avoiding over-determined chains of information and action should be intuitive if we understand it as a mandate to

minimize the amount of information the ABM requires from each agent when determining if they meet the criteria for an action. Returning to the “Traffic basic” model, we can consider the example of: the criteria for directing a driver-agent to decelerate. Without claiming that there is an ideal or “correct” set of relevant criteria, it is fair under **(a)** to say that a logic model which directs a vehicle-agent to slow by .25 speed-units if they are within a given distance of a leading vehicle is preferable to a logic-model which precisely calculates the amount of time-units before a vehicle-agent collides with a leading vehicle and then directs the vehicle-agent to slow by the precise amount of speed-units required to extend the time-to-collision by a further, precise amount of time-units.

Section 2.5.2 begins a discussion of the standard of explanatory power adopted for the ABM of TNC vehicle and passenger curb space behaviour developed in this thesis.

2.5.2 - ABM explanatory power

Wilensky and Rand identify three basic tiers of explanatory power for ABM research: verification, validation and replication. The latter two tiers are — acknowledging further levels of nuance which are not necessary here — intuitively similar to validation and replication in generic research design. Validation refers to confirming a given level of “fit” between the results produced by the ABM and the “real” world. Replication refers to the

reproduction of the researcher's results by independent scientists re-implementing the original ABM.

Both of the higher tiers of explanatory power were rejected as infeasible for this thesis. Replication was rejected because it requires a level of coordination with independent researchers which is outside the scope of the project.

Validation was rejected: first, because access to data of the scope and precision needed to validate TNC curb-space behaviour at the block-face level is restricted by TNC service providers; and second, because my review of ABM research in the transportation literature⁸ found that validation is uncommon, and does not preclude the production of valuable inference.

We will therefore confine our discussion here to ABM verification.

In brief, to verify an ABM is to confirm fit between the researcher's logic model, prepared in a format outside the coding language used to build the ABM, and the code of the ABM. This fit between the two distinct models is determined by comparing the micro-level rules for agent action outlined in the logic model and the micro-level rules written in the code of the modeling software.

Verification means establishing some level of certainty that the micro-level rules articulated in the researcher's natural / visual language logic model are accurately implemented in the micro-level rules of the code language model.

Wilensky and Rand identify several methods in the ABM literature which can be used for verification:

⁸ Discussed below in section 2.5.3.

- (i) An intermediary representation of the micro-level rules (e.g., a flow-chart);
- (ii) Unit testing, which refers to a component of the model which the researcher has designed to monitor a specified outcome or parameter and report if it passes a given threshold (e.g., a traffic model might include a unit test to warn if a vehicle-agent achieves a wildly unrealistic speed);
- (iii) Sensitivity analysis, which means searching for limiting specifications of parameters in the ABM that can cause the logic model to break down (e.g., a model of animal grazing behaviour might break down when the animal-agents are set to reproduce at every time-unit);
- (iv) Statistical analysis demonstrating that the ABM has not been over-determined, i.e., that it has not been specified to the point of simply reproducing a specific case of the research phenomenon in the “real” world.

The role of statistical analysis in ABM verification speaks directly to the nature and value of the “results” produced by ABM. It is in keeping with our above-made point that the value of ABM does not depend on the precise prediction of outcomes. An ABM should be run a number of times after the micro-level rules of the logic model have been fully implemented in the ABM’s code language. Further, it should be understood that multiple model runs are required *because* there is no canonical “result” of an ABM, where regression

modeling might produce a final result in its estimate of the coefficients for the research variables. The goal of ABM research is not to capture a final, determinate state into which the model has been proven to consistently resolve itself; such consistent resolution is rather a poor outcome. It indicates the model has been over-determined, specified too minutely, in order to mirror behaviour observed in the “real” world or produce a particular outcome. In ABM research, it is instead expected that, due to the organic nature of system-level phenomena generated by the simultaneous action of independent agents, running the model multiple times will produce occurrences with quantitative and qualitative outcomes that vary meaningfully. To the extent an ABM’s outputs can be described as similar to those of a regression analysis, the “results” are the regularly observed range of measured outcomes, together with a qualitative understanding of the systemic outcomes regularly observed.

The role of statistical analysis in verifying an ABM is to demonstrate that two sets of observed outcomes (say, the number of traffic collisions) are distinct enough that they are unlikely to have been drawn from the same statistical distribution. If a central risk in ABM analysis is that one may construct a logic model that intends towards generating a specific outcome, demonstrating that the logic model can produce outcomes of sufficient statistical difference can reduce the risk that we mistake an over-determined fixed outcome for the results of an organically operating system. To this purpose, Wilensky & Rand recommend either t-testing or the Kolmogorov-Smirnov test as basic means of statistical ABM verification.

A description of the specific method adopted for verification in the current project now follows.

(a) Flow-charts⁹ of the logic model and its constitutive micro-level rules for classes of agents were prepared. For Wilensky & Rand, this method (i) has its pre-eminent utility in scenarios where the subject-matter expert(s) developing the logic model's micro-level rules is not the individual(s) writing the rules in relevant ABM code. An intermediary representation that both parties understand can be a reference point for translating the two sets of rules. But for our purpose also, flow-chart representations of the micro-level rule sets have clear value. The charts first allow the reviewers on the thesis committee (and any reader) to see the flow of the logic model as a whole. The illustration of the intended relationships between the decision points in the logic model and the agent procedures implemented in the ABM then allows the reviewers to verify that the connections have in fact been established successfully. This component of model verification therefore depends on the subjective determination of the reviewers on the thesis committee with expertise in agent-based modeling.

We have so far developed a review of literature on the existing policy problems of TNC curb space behaviour; the set of policy interventions we will evaluate; the policy concerns which will guide our evaluation; the nature of the

⁹ Found in Appendix 2, below.

agent-based modeling approach adopted to inform our policy evaluation; and the methods used to confirm that the ABM developed has explanatory power. The literature review concludes with a discussion of other agent-based studies in the transportation field, specifically agent-based modeling of demand-responsive transportation (DRT). This last section of the literature review is what informed the specific decision points and criteria used in the logic model for individual agent behaviour. Section 3 then lays out that logic model in detail.

2.5.3 - ABM in recent transportation literature

We have previously established that agent-based modeling allows for the systematic representation and investigation of a logic model of individual behaviour by directing individual agents according to micro-level rules. The literature review did not develop a meaningful sample of efforts to model TNC curbspace behaviour with agent-based methods. It seems likely that, due to the recent explosion of demand for the mode, the question was not live in many researchers' minds until the past two-to-three years.

In order, therefore, to specify the micro-level rules by which my model of TNC curbspace behaviour proceeds, we review agent-based modeling of a similar, but more established, mode: demand-responsive transportation (DRT). DRT is here understood as a shared-ride point-to-point transit service, commonly (but not exclusively) para-transit, by which passengers can, through a dispatcher, either schedule a ride in advance or request a ride on-demand. (KFH 2008) The shared elements of point-to-point service and on-demand dispatching are what

drove the decision to use agent-based modeling of DRT as a reference point for modeling TNCs.

There are also clear dissimilarities between DRT and TNC services. Much of the difference stems from the historical circumstances of their origins. DRT in the United States was first developed as a para-transit solution for local and regional public transportation agencies.¹⁰ So, unlike TNC services, DRT is generally not operated as a for-profit enterprise. Further, while the two major TNC services in most American cities — Uber & Lyft — have international ambitions, DRT providers are generally not international or even national concerns. Because DRT services instead tend to be subsidiaries of larger transit agencies, they are often unique to the region in which they operate.¹¹ (Ronald et. al.) Modal differences can also extend to curb-space behaviour. TNC vehicles in some American cities are not required to provide ADA-compliant service. (e.g., City of Seattle 2014) Because DRT para-transit passengers require specialized procedures for boarding and alighting a vehicle, average curb-space dwell time can be significantly longer than for TNC vehicles. One study estimated total boarding and alighting time for each DRT passenger served at ~15 minutes; anyone who has observed TNC curb-space behaviour will see the difference. (Amirgholy & Gonzales)

These concerns introduce limitations in the direct applicability of existing practice in modeling DRT to the modeling of TNC services. This section next

¹⁰ See section 1.1 for more detail on the origin of American TNC services.

¹¹ Although both of these assumptions have been challenged in recent years by new for-profit market entrants (e.g., Chariot) operating independently or as component divisions of larger for-profit companies.

presents the elements in modeling which do appear to translate across modes, then discusses the approach used to meet the larger limitations.

Modeling DRT has largely considered optimization, meaning the development and testing of different routing and dispatching procedures (e.g., algorithmic routing) that can reduce passenger wait-time, travel-time and vehicle deadheading.¹² Agent-based modeling, however, is an exercise in simulation; there is generally not a single research variable or outcome being optimized. In their review of agent-based models of DRT, Ronald et. al. identify three sets of parameters commonly used to drive DRT simulations: **(i)** demand, **(ii)** supply, and **(iii)** environment. “Demand” here refers to parameters defining DRT’s passengers; “supply” to those defining vehicles; and “environment” to those defining the spatial environment in which both sets of agents act.

In the DRT models reviewed, the environment extends to a neighbourhood or larger intra-urban region. This requires specification of a transport (roadway) network; designation of loading-and other active curb-space use zones; and specification of background transport modes / behaviours. To simulate demand, a set of demand-agent (i.e., passengers) parameters are defined and determined. These commonly included: passenger modal intention; the presence and competitiveness of substitute modes; passenger wait- and in-vehicle time; corresponding elasticities relating wait times to modal substitution; and an

¹² “Deadheading” in this thesis refers to any time the vehicle is in operation with no passengers.

origin/destination (O/D) pair for each passenger. Parameters for supply-agents (i.e., vehicles) do not include intention, as the DRT vehicle does not need to make simulated choices about whether to provide service. Simulating supply instead requires vehicle attributes (e.g., size and speed); a means of accessing each passenger's O/D coordinates; and routing and dispatching procedures. None of the models reviewed were validated for fit against "real" world behaviour. (Ronald et. al.)

The current thesis project confines our research question to the curb-space behaviour of passengers (demand) and TNC vehicles (supply) at the block-face level (environment). This scope reduces the necessary number of parameters relative to the models of DRT reviewed by Ronald et. al., as passenger-agents in our model do not have a mode choice. But it is important to note that the DRT models reviewed consistently related passenger wait-time to impacts on modal choice. Ronald et. al. found that DRT models specified passengers as responding to longer wait times by being more likely to cancel a DRT ride request. This observation was used to justify the specification of our logic model to include a negative relationship between passenger wait-time and the likelihood that boarding occurs in the roadway.¹³

Routing and dispatching procedures in our research context are also significantly simpler than in the DRT models reviewed: vehicles traveling from one end of a block-face to the other do not face options for alternative routing

¹³ The exact relationship specified is detailed in section 3.1.

decisions beyond respecting the flow of traffic. The only significant routing concern is the vehicle's navigation into a load-zone (if one is utilized). Finally, although the set of parameters for the environment remains the same (roadway; curb-space uses; background traffic), their scope is reduced to reflect the smaller area of analysis.

But if these considerations tell us the sets of the modeling parameters required for an ABM of TNC curb-space behaviour, the modal differences between TNC and DRT noted above mean we cannot simply translate the specification of parameters in DRT models to a model of TNCs. In response to this gap, I participated in data collection for a research project (Goodchild & MacKenzie) conducted at the University of Washington Urban Freight Lab. After a week of observation of AM- and PM-commute peak in the study area, the project piloted a week-long intervention in the South Lake Union neighbourhood of Seattle, Washington. Curb-space in the study area was reallocated to increase the linear feet assigned for passenger load / unload and reduce the amount assigned for public parking. As a further (third week) intervention, the GPS routing interface used by TNC drivers picking up or dropping off passengers in the study directed some drivers to designated load / unload zones, instead of the location of their fare.

Goodchild & MacKenzie aimed to capture what, if any, effect on curb-space behaviour was occasioned by the intervention. Particularly valuable for our purposes, the study presents observed "compliance" rates — the rate at which

TNC loading operations occur in the street v. at the curb — before and after intervention:

- Pick-ups: before intervention, 20% was observed occurring in the street; after the second week's intervention, 12%.
- Drop-offs: before intervention, 16% in the street; after intervention, 11%.

These observed rates of occurrence for the loading behaviour we are modeling complement the more general best-practices found in our literature review of agent-based modeling of DRT. However, real-world loading operations often occur when a TNC vehicle is partially occupying a travel lane; a dedicated load zone; and / or a street parking space. Goodchild & MacKenzie's study thus faced the question of how to classify these partial events, while our ABM admits of only two classes of loading operations: in-roadway, or in a load zone. The compliance rates observed by Goodchild & MacKenzie therefore cannot directly specify our model, due to the differences in respective conceptual definitions of loading in the street. But, together with the subjective observations made during three ~2.5-hour periods over the morning (once) and evening (twice) peak commute, they informed our logic models of TNC-vehicle and -passenger behaviour. These logic models were in turn used to build the ABM. The following chapter (3) describes the resulting logic models. Their flow chart representations can also be found in Appendix 2.

(3) Logic models

This chapter (3) develops three sets of logic models and the policy matrix used to evaluate both modeled interventions. The logic models are grouped as follows. In section 3.1, **(i)** the properties of the environment are described; **(ii)** the parameters of the model; **(iii)** the global variables which all agents in the model can query. In section 3.2, **(i)** TNC passengers (drop-off & pick-up); **(ii)** private vehicles; **(iii)** TNC vehicles picking-up passengers; **(iv)** TNC vehicles dropping-off passengers. And in section 3.3, **(i)** traffic impacts; **(ii)** safety impacts. The policy evaluation matrix is laid out in section 3.4.

3.1 - Environment, model parameters and global variables

(i) Environment — The modeled environment of any NetLogo agent-based modeling software can contain some or all of three classes of agent-entity: “patches”, “turtles” and “links”. It will also always contain “the observer”, an agent controlled by the researcher.

Patches are individual square tiles laid out in a grid with dimensions defined by the researcher. Each patch has an x- and y-coordinate value, or “pxcor” and “pycor”, relative to the center point (0 , 0). Coordinates advance as in a standard Cartesian plane. Patches are capable of holding, changing and reporting a state of any property which the researcher can program using the NetLogo language; they can also interact with the states of other agents. The exception: patches do not move. In an ABM at our scale of analysis, they represent a ground surface.

“Turtles” are the most intuitively identifiable of these classes as being “agents”. Like patches, turtles can hold, change, and report states, as well as interact with the states of other agents. Unlike patches, turtles can also change

their position in the environment. Each turtle (non-exclusively) occupies a single “patch”. So at our scale of analysis, if patch agents are the “ground”, all the agents moving about on that ground are turtles.

Links connect, report and can alter the states of two or more agents, regardless of proximity. Links were not used in our ABM.

The environment for our ABM is generated when the “set up” button is pressed. A rectangular grid 16 patches tall and 50 patches wide is produced; the extents of the ABM’s coordinate system are therefore $-8 \leq y \leq 8$ and $-25 \leq x \leq 25$. This extent represents (not to scale) one block of a bi-directional, two lane arterial street with sidewalks and parallel parking / passenger loading bays adjacent to each travel lane. Each travel lane is one patch wide, as are the designated parking- and load-zones assigned in each scenario. The sidewalk on each side is three patches wide, or two on segments of the block where a pull-in bay is present.

The centerline of the roadway, marked in white, is the horizontal line of patches at $pycor = 0$. The east- and west-bound travel lanes are the patches at $pycor = -1$ and $pycor = 1$, respectively. Parking / load zones are patches with $pycor = 2$ or $pycor = -2$ and a subset of applicable x-coordinates, this subset being defined by the scenario being modeled. Parking spaces are marked in a randomized shade of light red. Load zone colouration varies by scenario. The sidewalk, at $pycors (-3 ; -4 ; 3 ; 4)$, as well as at $pycor (-2 ; 2)$ where parking / load zones are not present, are marked in a shade of grey. The sets of coordinates

for patches which are designated parking / load-zones are “global” variables, meaning all agents can access them at any time; besides this, and the above-mentioned use of pycor to indicate traffic flow, patches in this ABM do not have properties that interact with agents.

(ii) *Model parameters* — The interface of a NetLogo model can contain a number of inputs, defined by the researcher, for controlling the parameters of the simulation. In our ABM, these inputs and their functions are:

a. “Ped-speed” — This is a numeric value that defines the speed of passengers walking in the environment. Each ABM cycle, or “tick”, passengers (that are moving) move forward at their current heading by the specified value. Each patch is 1x1, so a passenger moving in a straight line drawn across the full distance of a patch with walk-speed of .2 will traverse the patch in 5 ticks.

b. “Acceleration” — Like ped-speed, this is a numeric value. It defines the amount of speed a vehicle agent will gain each tick, up to the vehicle’s top speed, if there is no blocking vehicle or pedestrian within a given distance of them.

c. “Deceleration” — This parameter is intuitively similar to acceleration. It defines the amount of speed a vehicle agent will lose each tick if it is within a given distance of a blocking vehicle or pedestrian.

d. “Max-vehicle-patience” — This is a randomly-determined numeric parameter of private vehicle agents used to indicate how much longer they

will wait before passing an idling vehicle in the street.

e. “Min-pass-patience” — “Patience” is also a numeric parameter of passenger agents used by the ABM to determine whether the passenger wants to board in the street or at a load zone. When a passenger’s TNC arrives, their remaining patience is checked against this parameter to determine if the passenger will try to board in the roadway or at a load zone.

f. “Number-of-private”; “number-of-passengers”; “number-of-parked” — These numeric parameters each define the maximum number of each type of agent (private vehicles; passengers; parked vehicles) which may be present at one time. Note that in the case of parked vehicles, the ABM always spawns the maximum number at set up.

g. “Mean-wait-time” and “SD-wait-time” — The number of ticks a passenger waits for their TNC to arrive is determined by selecting a random value from a normal distribution. These two parameters define the mean and the standard deviation of that normal distribution.

h. “Mean-pass-patience” and “SD-wait-time” — Each passenger is randomly assigned an initial patience value from a normal distribution; these two parameters define the mean and standard deviation of that distribution.

i. “Mean-park-time” and “SD-park-time” — When private vehicles park in the study area, they set a length of time (number of ticks) that they will be parked before getting back on the road. This time is randomly assigned from a normal distribution; these two parameters define the mean and standard deviation of that distribution.

(iii) *Global variables* — Many NetLogo models specify a set of “global” variables, or variables which any agent can query at any time. In our ABM, these global variables are:¹⁴

- a. “Lanes” — This is the set of the pycor of the two travel lanes, i.e., (-1 ; 1).
- b. “Walk” — This is the set of the pycor of the sidewalk, i.e., (-4 ; -3 ; -2 ; 2 ; 3 ; 4).
- c. “Load-zone” — The set of the pxcor of loading zone areas, which differs for each scenario. The pycor of loading zones are always -2 (east-bound lane) or 2 (west-bound lane).
- d. “Parking” — The set of pxcor of patches allocated for public parking. This is always a subset of the set “load-zone”.
- e. “Turning” — The set of pxcor of patches that are adjacent, directly behind, and directly ahead of, patches that are marked as load zones. This variable is used by vehicle agents that are turning into and out of load zones — as drivers use mirrors — to check for other agents in the roadway.
- f. “Passenger-IDs” — The set of whole numbers available for each passenger agent’s unique passenger-ID. This set is generated using the NetLogo language “range” function, which reports a range of whole number

¹⁴ N.B.: there are also 8 global variables used by the ABM as “pools” into which agents can report instances of the events which we are treating as impacts. These variables therefore report the observed number for each type of impact across an ABM run. They are described in detail in section 3.3 below.

integers beginning with 0 and ending 1 step less than the value specified by the ABM's "number-of-passengers" parameter. E.g., if "number-of-passengers" is set to 4, the "Passenger-IDs" global variable will contain the set of integers (0 , 1 , 2 , 3) at set-up.

g. "TNC-arrival" — This is the set of passenger-IDs for passenger agents whose "wait-time" has reached 0. When a TNC vehicle performing a pick-up spawns, it is randomly assigned a passenger-ID from this pool (which ID is then removed from the pool).

In section 3.2 below we develop narrative representations of the logic models for the passenger and vehicle agents that interact in, and with, the environment we have just described.

3.2 - Passengers and vehicles

(i) *Passenger agents (see fig. 2 in Appendix 2 for flow charts)* — In our ABM passengers are a "breed", or subclass, of turtle agent named "pass", singular "a-pass". They are represented using the default turtle shape with a randomized shell colour:



Image 1 - passenger agents

When the model is “set up”, the environment and global variables described in section 3.1 above are generated, with curb-space allocation according to whichever intervention scenario has been selected.¹⁵ Passenger agents are not created at set up. Instead, at the start of each “tick”, or model cycle, the model rolls a random number generator with range 0 - 99. If the model rolls 99, and the number of existing passengers is less than a maximum value specified by the observer interface parameter “number-of-passengers”, the model creates a passenger agent. Unless the limit is reached, then, there is a 1% chance every model cycle that a passenger will spawn.

When the model creates a passenger agent it assigns a value to a number of the agent’s properties. I describe each below, followed by a narrative and flow chart description of the logic model:

- a. “Direction” — This is a binary property used to identify the direction which a passenger being picked up wants to travel, east (1) or west (-1). The

¹⁵ See chapter (4) for the specifications of each intervention scenario.

model randomly assigns the value of this property when each passenger agent spawns.

b. “Walk-speed” — As described in section 3.1 under **(ii)**, when passengers “walk” forward at a given heading they travel a distance = the “Speed” parameter every tick.

c. “Passenger-ID” — As referenced in section 3.1 **(iii)**, each passenger being picked up is assigned a numeric ID from the pool generated on set up. TNC agents that are dropping off passengers are also assigned unique IDs from the same pool. The pool therefore acts as a cap on the number of pick-up / drop-off agents that can be active in the model at one time — if there are no unique IDs remaining, these agents won’t spawn. When a passenger agent leaves the simulation area, i.e., “dies”, their ID is returned to the pool of available IDs, allowing new agents to spawn.

d. “Hatched?” — This is a binary property set to (0) if the passenger is being picked up, and (1) if they were dropped off (“hatched” refers to the NetLogo command, “hatch”, used to spawn the passenger agents who have been dropped off). It is used by the model to direct passenger agents to their relevant sub-procedures for motion.

e. “N-S” — This is a binary property set only for passenger agents being picked up. It is set to (0) if the agent spawns on the south side of the roadway, and (1) if on the north. It is used by the model to direct the TNC agent picking

up the passenger agent to the relevant sub-procedures for motion.¹⁶

f. “Wait-time” — As described above under **(ii)**, when a passenger agent spawns the model assigns them a wait-time value chosen at random from a normal distribution with mean = the “mean-wait-time” parameter and standard deviation = “SD-wait-time”. Random selection from a normal distribution was used to ensure an element of randomness in each passenger’s wait time while respecting the intuition that TNC services aim to provide service at a level that is relatively consistent within a given time period.

g. “Patience” — as referenced in section 3.1 under **(ii)**, this value affects the model’s determination of whether a passenger will board their vehicle in the roadway or at a load zone. When a passenger agent spawns the model assigns them a patience value randomly chosen from a normal distribution with mean = “mean-pass-patience” and standard deviation = “SD-pass-patience”. Random selection from a normal distribution was used to ensure an element of randomness in each boarding operation.

h. “In-roadway” — This is a numeric property with two uses. First, until the passenger’s TNC “arrives”, it is set to (2). This indicates to the model’s procedure for passenger motion that the passenger’s TNC has not arrived. Once the TNC agent arrives, the value of this property is re-determined, based on a check of the passenger’s remaining patience against the value of

¹⁶ This variable does pass information about the passenger agent to their TNC agent, but this appears to be a reasonable case, in that the routing application used by “real” TNC drivers to locate their passengers indicates this same information to the driver.

the observer interface parameter “min-pass-patience”, to indicate to the model that the passenger agent wants to load in the street (0) or at a load zone (1).

Each tick, there is a chance¹⁷ of the model spawning a passenger agent for pick-up or drop-off with properties determined as above. These passenger agents spawn at a randomly selected empty patch within 4 patches of the x-origin ($pxcor = -4 \longleftrightarrow pxcor = 4$). At spawn, their heading is set towards a random load zone on their side of the roadway and in the direction that they wish to travel — e.g., if the passenger spawns on the north side of the study area and wishes to travel east, their heading will be set towards a load zone in the northeast quadrant of the model.

The logic model for passenger pick-up behaviour can then be broadly grouped into two moments, *before* and *after* their wait-time reaches 0 and their TNC spawns.

Each tick in the *before* period, passengers reduce their patience and wait-time values by 1. If their y-distance from the curb is $> .25$, they will walk forward along the heading set at spawn (i.e., towards a load zone). On the tick where a passenger’s wait-time reaches 0, the ABM checks the remaining value of the passenger’s patience property against the “min-pass-patience” model parameter. If the value of the passenger’s patience is greater, the passenger will want to load in the load zone, and the passenger’s “in-roadway” property is set to (0). In the

¹⁷ Determined by the model period set using the observer interface, as described below and in section 4.1.

alternative, the passenger will want to load in the street, and “in-roadway” is set to (1). The model then passes the passenger’s passenger-ID to the “TNC-arrival” global variable. Later in the same tick, the model will spawn a TNC with the same passenger-ID and remove the ID from the global variable pool.

This begins the *after* period. If $\text{in-roadway} = 0$ (passenger is still patient and wants to load at a load zone), the passenger will wait at or near a load zone until the TNC agent is within 1 distance, at which point they will walk towards it. If $\text{in-roadway} = 1$ (passenger has lost patience and wants to load in the roadway), once the passenger’s TNC is within 5 of the passenger and has stopped in the roadway or otherwise reports a speed less than the passenger’s speed, the passenger will walk towards the TNC.

This logic changes only if $\text{in-roadway} = 0$, with the matching TNC agent in the correct travel lane for the passenger’s desired direction, but the passenger on the opposite side of the street (e.g., passenger’s “direction” is 1 (east) and the TNC is in the east-bound (south) travel lane ($\text{ycor} < -1$), but the passenger is on the west-bound (north) side of the roadway ($\text{ycor} > 1$)). In this case, the TNC agent will “ask” the passenger agent to cross the road and load in the correct travel lane (i.e., set “in-roadway” = 1). This is meant to represent informal (waving; eye-contact) as well as formal (an in-app message; a phone call) methods of communication between drivers and passengers to increase travel efficiency in this common¹⁸ loading behaviour scenario.

¹⁸ Based on my own observations during the period of the Goodchild & MacKenzie study.

In any of these sub-cases, on the first tick where the passenger is on the same patch as the TNC, the passenger reports its ID back to the “passenger-IDs” global variable (so another passenger can later spawn with this ID). Before the next tick, the passenger then “dies”, i.e., is removed from the simulation, to represent their having boarded the vehicle.

This completes the passenger logic model for pick-ups. The logic model for drop-offs is simpler. When the agent is “hatched”, i.e., alights from their TNC vehicle, the ABM sets their heading towards one of two patches: (0, 4) or (0, -4). These patches are taken to represent building entrances. There is an 80% chance the agent will be assigned a heading towards the building entrance on their side of the road, which is to say, there is a 20% chance they were dropped off on the wrong side of the road. Whichever heading they are assigned, they will then walk forward at the value of “walk-speed” every tick until they reach a building entrance, at which point they enter the building and leave the study area (“die”).

(ii) *Vehicle agents* — There are three subclasses, or “breeds”, of turtle agents used to represent vehicles in our ABM:

- “Park”, singular “a-park” — vehicles parked in public parking. At set-up, the ABM places a number of these agents (= the value of the parameter “number-of-parked”) in a randomly chosen patch that has been designated as a load zone. These agents do not move or interact with other agents beyond blocking their respective parking / load zones for the duration of the model

run. Therefore, no logic model is presented for them.

- “Private”, singular “a-private” — private vehicles that traverse the study area and either simply leave or (attempt to) park, wait, and then leave.

These agents are not placed at set up.

- “TNC”, singular “a-TNC” — vehicles providing TNC service to passengers, capable of both pick-up and drop-off behaviour, in-roadway or at a load zone. These agents are also not placed at set up.

Each class of vehicle agent is represented with the standard NetLogo “car” shape. “Private” cars are a shade of red; parked cars are grey; and TNC vehicles (drop-off and pick-up) blue:

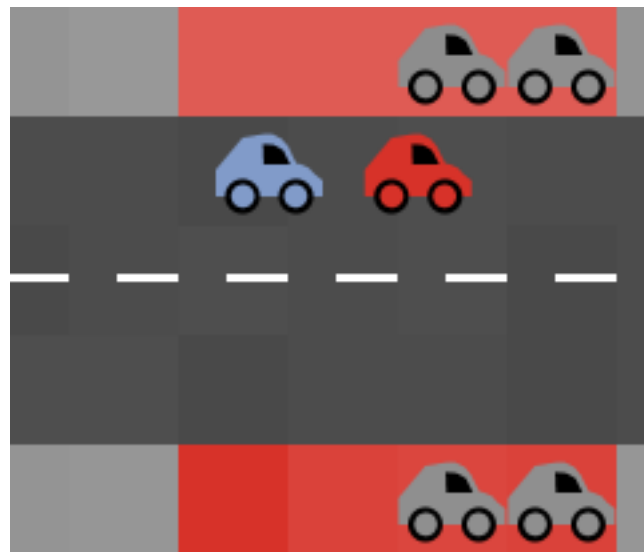


Image 2 - vehicle agents

The properties of “private” and “TNC” vehicle agents, together with narrative descriptions of their respective logic models, are as follows.

Private vehicles (see figs. 3 & 4 in Appendix 2 for flow charts):

a. “Speed” — This numeric property records the current speed of the car. Each tick (after accelerating / decelerating / reducing speed to 0 (idling)), the car will move forward by this value. The initial value of this property is randomly determined up to a value .05 less than “top-speed”.

b. “Top-speed” — This randomly determined numeric property records the maximum possible value of the “speed” property. It is capped at $(0.17 + \text{a random integer} \geq .05)$.

c. “Patience” — This numeric property records the current patience of the vehicle agent. Patience is used to determine how long a private vehicle will wait behind an idling TNC before attempting to pass them by traveling in the center of the roadway.

d. “E-W-spawn” — This binary property records on which side of the road the vehicle originally spawned, east (1) or west (-1). It is used in the passing procedure so that the ABM knows which direction the vehicle wants to travel even when they are not in the correct travel lane.

e. “Is-parking?” — This property is set at agent spawn to indicate to the ABM whether the agent wants to park in the study area (1) or not (0). There is a 0.33% chance of this being set to 1. If the vehicle does park, it is then set to (2); when the vehicle’s parking time is up, it is then set to (0).

f. “Park-time” — This property records the number of ticks a private

vehicle agent will stay “parked” before heading back on the road. As described above in 3.1 (ii), the value is randomly chosen by the ABM at the time of parking from a normal distribution.

Each tick, there is a 1% chance of the model spawning a private vehicle agent with properties as described above. The vehicle will spawn at the origin of one of the two travel lanes, and will either be seeking to park, or not. There are thus two broad moments of the logic model for these agents.

Private vehicles that *are not seeking to park* attempt to move forward every tick. They first compare their speed to their top speed, and accelerate by “acceleration” if their current speed is less than. If there is no blocking agent with a distance of $(1 + \text{speed})$, they will then move forward in the appropriate direction by the value of their speed property. If there is a blocking agent that is not idling, the private vehicle agent will reduce their speed to below that of the blocking agent. If there is a blocking agent that *is* idling, the private vehicle agent will set their speed = 0 and lose one “patience”. If there is an idling blocking agent and the private vehicle’s patience is = 0, the private vehicle will attempt a “passing procedure”.

In the passing procedure, the private vehicle moves into the center of the roadway ($y_{\text{cor}} = 0$) and moves forward in the direction of travel for the travel lane they previously occupied (as referenced above, the property “E-W-spawn” is used to record the prior direction of travel). Each tick, they will continue to move forward in the center lane until the patch to their immediate right is empty, at which point they will merge back into their previous travel lane.

Private vehicles that *are seeking to park* share all of the behaviours described above, with the addition that, if they pass an empty parking spot (an unoccupied patch with a *pxcor* value that is a member of the global variable set “parking”), they will leave their travel lane and park in it. Once parked, the agent’s “is-parking?” value will change to (2), and the ABM will assign the agent a “parking-time” by drawing randomly from a normal distribution defined via the observer interface. This parking time value will be reduced by 1 every tick; at 0, the agent will check for blocking agents and (if there are none) exit the parking space back into traffic. The agent then obeys the procedure for motion described in the paragraph above.

In any of these sub-cases, private vehicle agents will eventually reach the opposite boundary of the study area from that at which they spawned. At this point, the agent leaves the study area (“dies”) — and, if the vehicle was not able to park (i.e., the agent’s “is-parking?” still = 1), this is reported to the ABM as an impact.

TNCs:

a. “Speed” — This numeric property records the current speed of the car. Each tick (after accelerating / decelerating / reducing speed to 0 (idling)), the car will move forward by this value. The initial value of this property is randomly determined to a value that is up to .05 less than “top-speed”.

b. “Top-speed” — This numeric property records the maximum possible value of the “speed” property. It is randomly determined at agent spawn.

N.B.: TNC agents have a maximum possible top-speed of .17 at spawn, where for private vehicles the maximum is .22. TNC vehicles increase their top-speed value by .05 after boarding operations. This is meant to reflect the intuition that TNC vehicles drive more slowly when looking for or dropping off their passenger (e.g., while looking out the window; at a GPS display; or for a load zone) than they do after conducting loading operations.

c. “Target-lane” — This binary property indicates the travel lane in which the TNC agent currently wishes to travel, east (-1) or west (1). Initially set to mirror the travel lane in which the agent spawns, but can change based on the location of the TNC’s passenger. Because TNC agents performing drop-offs do not change lanes, this variable is only used by the ABM in reference to pick-ups.

d. “Passenger-ID” — As described above, each TNC agent is assigned a numeric ID at spawn: pick-up agents are assigned an ID number from the global variable “TNC-arrival”, which will match that of a passenger whose “wait-time” has reached 0. Drop-offs are assigned an ID from the global variable “passenger-IDs”, which is unique to the agent.

e. “Full” — This numeric variable has four possible states, two for pick-up vehicles and two for drop-offs. Pick-ups can either be empty (0) or full (1); drop-offs are either full (3) or empty (4). Each value indicates to the ABM a distinct sub-procedure for motion which the agent should take.

f. “Direction” — This binary property is used by pick-ups to record the direction the agent’s matching passenger agent wishes to travel, east (1) or

west (-1).

g. “Travel-time” — As referenced above in 3.1 (iii), a normal distribution defined by “Mean-wait-time” and “SD-wait-time” is used to determine the time before each TNC agent “arrives” (spawns) in the study area. The same normal distribution is used to determine the “wait-time” for passenger agents awaiting pick-up (as described above in this section) as is used to determine the “travel-time” for TNC agents performing drop-off.

h. “Patience” — This property is used by TNC agents performing drop-off to check if the passenger in the vehicle wants to alight in the roadway or at a load zone. Its initial value is determined in the same manner (using the same normal distribution) as that of the patience of passenger agents waiting for pick-up.

i. “My-zone” — This numeric property indicates the pxcor of the load zone closest to the TNC’s passenger. It is used by the ABM to direct the TNCs performing pick-ups when to pull out of the travel lane and into a load zone.

j. “Mycor” — This numeric property is used by TNC agents performing pick-ups to indicate to the ABM on which side of the road their passenger is waiting.

k. “In-roadway” — This binary property is used by TNC agents performing drop-offs to indicate to the ABM whether their passenger wants to alight in the roadway (1) or at a load zone (0).

Each tick, there is a 1% chance of the ABM calling the “create-passengers”

procedure. This procedure in turn has a chance of generating either a passenger for pick-up (“create-pick-ups”) or TNC agent for drop-off (“create-drop-offs”). The likelihood of each depends upon the “Period” chooser on the observer interface: if the period is set to “AM”, there is a ~88% chance of each “create-passengers” call creating drop-offs; for “PM”, there is a ~90% chance of the call creating a passenger for pick-up. This proportional make up of TNC demand in each commute period was set to roughly match the demand patterns observed in the Goodchild & MacKenzie study period.

Drop-offs (see figs. 5 & 6 in Appendix 2 for flow charts)

Drop-off agents spawn in the ABM when the “create-drop-offs” procedure is called by “create-passengers”. The agents are initially invisible, and placed outside the study area (in the green patches above $y = 5$). The agents are given a “travel-time” and “patience” value, as described above. These values are then reduced by 1 each tick; when “travel-time” = 0, the ABM will call “drop-off-arrive”, which makes the TNC agent visible and moves it to a random end of the roadway. At the same point, the agent’s remaining “patience” value is checked against the observer interface parameter “min-pass-patience”. If the agent reports a value greater than this parameter, the agent’s passenger will alight at a load zone (the TNC agent will set “in-roadway” = 0); if less than, the passenger will alight in the roadway (“in-roadway” = 1).

At this point, there are two broad moments in the logic model for drop-off agents: before, and after, the vehicle’s passenger has alighted.

Before the drop-off agent's passenger has alighted ("full" = 3), the TNC is either seeking to drop its passenger off in the roadway, or at a load zone. If loading is to occur in the roadway, the TNC will proceed in the direction as described above under "Private vehicles" (with the exception that TNC agents do not attempt to pass other agents). Once the TNC is on one of the center patches of the model, the ABM vehicle will call the agent to "alight", idling the agent and "hatching" (spawning) a passenger agent on the same patch. If, on the other hand, the passenger wants to alight at a load zone, the TNC drop-off agent will proceed down the roadway until it is parallel with an empty load zone. If this latter is this case, it will pull into the load zone and the TNC agent will be called to "alight" as above.¹⁹ If the vehicle travels the length of the study area and does not pass an empty load zone, it will be called by the ABM to "alight" near the end of the study area. This inability to access a load zone when desired is reported to the ABM as an impact.

In each of the above sub-cases, when the passenger "alights", the TNC agent reports its passenger-ID back to the global variable "passenger-IDs", so that the ID is available for subsequent calls of "create-passengers".

After the drop-off agent's passenger has alighted ("full" = 4), the TNC will either be in a load zone or in the roadway. If the vehicle is in the roadway, it will idle for 10 additional ticks after performing the drop-off; if it is in a load zone, it will

¹⁹ N.B.: It is assumed a TNC vehicle can use an empty parking space or load zone equally as a load zone.

idle up to 150 ticks. If the agent is in a load zone, it will check for blocking agents and (if there are none) pull into the roadway. Once the agent is in the roadway, it will proceed to move in the direction of traffic as described above under “*Private vehicles*” (with the exception that TNC agents do not attempt to pass other agents). The vehicle exits the study area (“dies”) once it reaches the edge of the roadway.

Pick-ups (see figs. 7 & 8 in Appendix 2 for flow charts)

As referenced above in the sub-section covering passenger agents, a TNC agent will spawn in the study area at a randomly determined end of the roadway when a passenger agent’s “wait-time” has been reduced to 0. To link the two in the ABM, the TNC agent’s “passenger-ID” is set to match the ID of a passenger whose wait-time = 0. The procedures that follow can then be separated into two moments. (1) the TNC agent has spawned in the travel lane corresponding to the passenger’s desired direction of travel (reported by “direction”), or (2) not. Each moment has their own two subdivisions — (n.1) the passenger is on the same side of the road as the TNC, or (n.2) not.

(1.1) If the TNC agent *is in the passenger’s desired travel lane* (i.e., the value of the agent’s “direction” property = $-(y_{cor})$), then the TNC agent will stay in this travel lane. Motion down the travel lane will initially proceed as described above for private vehicles (with the exception that TNC agents do not attempt to pass other agents). If the TNC’s matching passenger agent *is on the same side of the road*, the TNC agent will set its “my-zone” property to the px_{cor} of whichever empty

load zone is closest to the passenger. If the $pxcor$ of the patch to the TNC's immediate right matches the value of "my-zone" (i.e., the TNC is parallel to the given load zone), the TNC will pull into the load zone. If the given load zone is not to the right, the TNC will proceed down the roadway — unless its matching passenger is within 2 distance, in which case it will idle and wait for the passenger to board.²⁰

(1.2) If, alternately, the TNC agent *is in the passenger's desired travel lane* but the TNC's matching passenger agent *is not on the same side of the road*, our logic model assumes both the passenger and the driver would prefer to conduct loading operations in the preferred travel lane (so as to avoid making two U-turns in quick succession). The ABM will therefore ask the passenger agent to set its "in-roadway" property to 1, and the TNC agent will proceed in its original direction down the roadway. Once the TNC agent is within 2 distance of its matching passenger, it will idle and wait for boarding.

(2.1) In the second moment, the TNC agent *is not in the passenger's desired travel lane* (i.e., the value of the agent's "direction" property = $ycor$). Motion down the travel lane will initially proceed as described above for private vehicles (with the exception that TNC agents do not attempt to pass other agents). If the TNC's matching passenger agent *is on the same side of the road*, behaviour proceeds as described above (1.1).

²⁰ Note that the order of operations here means a TNC agent will *not* idle in the roadway waiting for a passenger if it is parallel to its desired load zone — even if the passenger is within 2 distance. This is meant to reflect a certain level of indeterminacy and potential for conflict between the driver and passenger agent's intentions in the period where they are in close proximity to both each other and a load zone.

(2.2) The pattern changes, however, if the passenger *is not on the same side of the road*. If the TNC has driven past the passenger agent and the distance to the passenger is > 2 — which generally occurs if the passenger wants to load at a load zone, and so has not attempted to intercept the car in the roadway — it will make a U-turn by inverting its “target-lane” variable. Motion will then proceed as described under (1.1). If the TNC has not driven past the passenger, it will proceed down the roadway in the direction of its travel lane until it is intercepted by the passenger (distance < 2), at which point it will idle and wait for boarding.

In all four of these cases, once the passenger has boarded, the TNC agent sets its “full” property = 1. If the vehicle is in the roadway, it will idle for 10 additional ticks after performing the pick-up; if it is in a load zone, it will idle up to 150 ticks. If boarding occurred on the side of the road corresponding to the passenger’s desired direction of travel, the TNC will proceed down the roadway in the direction of traffic (after pulling out of a load zone, if applicable). If boarding occurred on the opposite side of the road from the desired direction of travel, the TNC will make a U-turn by inverting the value of its “target-lane” variable, after which it will proceed in the direction of traffic. Finally, at the edges of the study area, the TNC agent will exit (“die”).

This completes the set of logic models for agents in our ABM. The next section 3.3 lays out logic models for the impacts we identified in section 2.2 above. Chapter (3) then concludes with a policy evaluation matrix, systematizing the

evaluative criteria developed in section 2.4.

3.3 - Logic models for ABM reporting of impacts

Our literature review identified four quantifiable impacts valuable for evaluating interventions like those proposed by Fehr & Peers:

- (i) vehicles unable to access a parking space / load zone;
- (ii) the rate and number of loading operations occurring in the roadway
- (iii) unsafe vehicle passing maneuvers (passing both pedestrians and other vehicles)
- (iv) Amount of time vehicles are observed queuing or slowed behind a slower / idling vehicle

The ABM developed for this project quantifies these impacts, as well as by reporting to the researcher each instance in which a defined state of affairs in the ABM occurs. These states of affairs are defined in reference to the logic models developed in this section.

(i) Vehicles unable to access a parking space / load zone — As indicated in the above section 3.2, these impacts are reported when an vehicle agent reporting a property-state that indicates they wish to access a parking spot or load zone has traveled the length of the study area without finding a spot. There are three classes of vehicle agents to which this may apply: private vehicles seeking to park (“is-parking?” = 1); TNC pick-up agents whose passenger does not have access to a load zone; and TNC drop-off agents whose passenger wished to alight at a load zone (“in-roadway” = 0). Reporting for this impact occurs on the model

cycle when: private vehicle agents seeking to park exit the study area without parking; TNC agents performing a pick-up are unable to find an empty load zone on the same side of the street as their passenger; and, when drop-off agents seeking to use a load zone instead alight their passenger in the roadway.

Because a failure to access a parking / load zone when desired has different policy implications for the one mode (private vehicles) than the other (TNC vehicles), these impacts are reported separately. If a private vehicle is unable to park, (1) is added to the global variable “no-free-parking”. If a TNC agent is unable to find a load zone, (1) is added to “no-free-zone”.

(ii) The rate and number of loading operations occurring in the roadway — The two classes of loading operations — boarding and alighting — occur when the ABM calls agents that fulfill the criteria for the procedures “board” and “alight”. Quantifying this impact therefore requires capturing the number of times agents are called by these procedures while in the roadway. There is still, however, an element of the researcher’s discretion in this metric, in that “the roadway” can be understood more or less conservatively. The relevant impact could be defined as occurring only when the ABM calls agents to “board” and “alight” within $-1 \leq ycor \leq 1$, meaning the vehicle was wholly in the travel lane. Or it could be defined more liberally as occurring whenever the agents called are within $-2 < ycor < 2$, including loading behaviour from a vehicle agent partially within a load zone as an impact. Because the dimensions and angles of movement modeled in our ABM are not to scale, this study adopts the more

conservative interpretation of “the roadway” out of an abundance of caution.

When an agent boards or alights in the roadway, the ABM adds (1) to the global variable “in-roadways”. At a load zone — “At-load-zones”.

(iii) Unsafe vehicle passing maneuvers — It is assumed that every attempt by a private vehicle agent to pass an idling TNC using the center of the roadway introduces new potential for conflict with other agents. Every time the ABM calls a private vehicle to complete a “passing-procedure”, therefore, is captured as an example of this category of impact — (1) is added to the global variable “Passes”. In addition to this, an impact is captured every time a vehicle agent attempts a maneuver of any kind that is blocked by a passenger agent. Every ABM cycle a vehicle agent is called to move, but finds a blocking passenger agent in the roadway or *in* a loading zone ($y_{cor} \leq 2$ or $y_{cor} \geq -2$), (1) is added to the global variables “passes” and “ped-passes”. This latter is meant to reflect the additional potential for conflict introduced when a vehicle attempts a maneuver in close proximity to a more vulnerable user.

It should also be noted, however, that this metric is potentially quite sensitive to the observer interface parameter “max-vehicle-patience”, which defines the maximum amount of patience with which a private vehicle agent will spawn, and thus the maximum length of time one of these agents will idle before attempting a passing maneuver. To control for this concern, the researcher should be clear that the rate of this impact under one scenario is only to be

compared to scenarios with an equivalent “max-vehicle-patience” parameter.²¹

(iv) Amount of model uptime when vehicles are queuing or slowed in the roadway — This impact is reported when a vehicle idles or travels slowly in the roadway and other agents are forced to slow or queue at speed = 0 behind it. There are several points in our logic models at which the ABM may call agents to slow or set speed = 0. TNC agents may be called to idle because their passenger is within distance 2 and they are waiting for the passenger to board. However, private vehicle agents are never called to idle unless the blocking car ahead of them is at or below speed = 0; queuing time is therefore always (at least) indirectly a consequence of an idling TNC vehicle agent. The ABM therefore captures this impact by adding (1) to the global variable “Queuing” every time a vehicle agent is called to slow or set speed = 0, excluding cases where the idling agent is a TNC agent with matching passenger agent within distance 2.

(v) In order to facilitate comparison with the observations made in the Fehr & Peers study, an additional metric was captured — number of private vehicles parking on the block face. This metric is reported every time a private vehicle agent has successfully left the roadway and entered an empty parking space. In the ABM, this is captured by adding (1) to the global variable “public-parked” on the first model cycle that a private vehicle wishing to park is in a parking spot (at

²¹ ABM runs informing this study set the “max-vehicle-patience” parameter at 15.

ycor = 2 or ycor = -2).

These ABM outputs, together with qualitative inferences drawn from observing the model, make up the data informing our policy evaluation of the interventions proposed by Fehr & Peers. The next section 3.4 shows an evaluation matrix linking these outputs to the evaluative criteria developed from *CoS 2035* in section 2.2. Chapter (4) then gives the specifics of each intervention scenario modeled using the ABM, after which we will (in chapter (5)) evaluate scenarios using the matrix and in reference to different land use contexts.

3.4 - Policy evaluation matrix

In section 2.4 above, we developed five evaluative criteria from transportation goals and policies in *CoS 2035*. They were:

- (i) increased the number of drop-offs on a block-face in a retail district (“customer access”)
- (ii) decreased the number of in-street drop-offs on a block-face where current curb-space allocation conflicts with efficiently serving the predominant modal activity
- (iii) the potential for conflicts between two vehicles and between vehicles and pedestrians
- (iv) conflicts with the land-use context or plans for modal infrastructure
- (v) if it unduly raises the competitiveness of one mode where modal planning had intended the priority of another.

Likewise in the preceding section 3.3, we developed four quantitative impacts to be directly measured and reported by the ABM:

- (i) vehicles unable to access a parking space / load zone;
- (ii) the rate and number of loading operations occurring in the roadway
- (iii) unsafe vehicle passing maneuvers (passing both pedestrians and other vehicles)
- (iv) number of vehicles observed queuing / idling behind an idling TNC vehicle

The matrix below describes in qualitative terms the conclusion we reach, under each criterion, as the ABM-reported magnitude of each quantitative impact *increases*. These conclusions are in turn reversed as the magnitude of each quantitative impact decreases.

The matrix allows each intervention modeled in this study multiple and at times conflicting dimensions of evaluation. A decline in one metric (e.g., unsafe vehicle passing) and concomitant improvement under a given criterion (e.g., the potential for conflicts) may be concurrent with a spike in another metric (e.g., private vehicles unable to park) and concomitant decline under a second criterion (e.g., a mismatch between curb space allocation and predominant use). Our evaluation is therefore not intended to produce a clear policy decision (“go / don’t go”), but rather to enhance stakeholders’ understanding of the trade-offs each intervention may occasion. In chapter (5), evaluation of the metrics reported by the ABM under each intervention scenario is therefore presented together with a qualitative discussion of the relative importance of the results for several land-use contexts.

The next chapter (4) lays out the specific parameters of the scenarios used to model each intervention.

Policy evaluation - matrix

Metrics

Criteria

	VEHICLES UNABLE TO ACCESS PARKING SPACE / LOAD ZONE	RATE & NUMBER OF LOADING OPERATIONS OCCURING IN THE ROADWAY	UNSAFE VEHICLE MANEUVERS	VEHICLES QUEUING / IDLING BEHIND A SLOWER VEHICLE	SUMMARY
COMPETITIVENESS OF THE TNC MODE FOR MODE SHARE (T 2.2; T 2.5)	<p>Minor negative impacts if TNC vehicles are frequently blocked from load zones.</p> <p>Minor positive impacts if private vehicles are unable to park.</p>	<p>Minor negative impacts. Although loading in the roadway introduces a higher potential for conflict with other users, observation of current behaviour suggests this is generally not a significant disincentive to use of the mode.</p>	<p>Minor negative impacts when vehicles pass other vehicles, as this reflects potential for an indirect conflict between a TNC passenger and a vehicle. Negative impacts from vehicles passing pedestrians, as these maneuvers reflect potential for a direct conflict between a vulnerable user and a vehicle.</p>	<p>Positive impacts, as this behaviour reduces the speed and reliability of other modes without impacting the passenger’s perception of service.</p>	<p>Our metrics can capture general impacts to the competitiveness of the TNC mode, but lack the specificity to drive quantitative conclusions. Evaluative conclusions about the desirability of impacts to mode share, however, depend on land-use and modal-plan context, and should therefore be developed qualitatively.</p> <p>We can conclude that there may be a misalignment between curb space allocation and predominant modal patterns if TNC vehicles or private vehicles are frequently unable to access a parking / load zone when desired.</p>
MISALIGNMENT BETWEEN ALLOCATION AND PREDOMINANT USE (T 3.18)	<p>Negative impacts if a significant number of users of either mode is unable to access its preferred curb space use.</p>	<p>Minor negative impacts if observed independently of a meaningful proportion of TNC vehicles trying, but unable, to access a load zone. Negative impacts if observed together with the same.</p>	<p><i>No impact</i></p>	<p>Minor negative impacts if this is observed together with a meaningful proportion of TNC vehicles loading in the roadway. No impact otherwise.</p>	
POTENTIAL FOR CONFLICTS (TG 2; T 2.3; T 2.5)	<p>Minor negative impact from inability to access load zone, as there is the potential to push more loading activity into the roadway.</p>	<p>Negative impact, as loading in the roadway is taken by definition to increase the potential for conflicts.</p>	<p>Negative impact, as vehicle passing in the center of the roadway is taken by definition to increase the potential for conflicts (especially when pedestrians are present).</p>	<p>Negligible-to-minor negative impact. Increased vehicle queuing is likely to produce an increase in unsafe passing maneuvers, but this impact is already captured distinctly.</p>	<p>Our metrics can capture significant changes in the extent of impacts to the potential for conflicts.</p>
CUSTOMER ACCESS & ACTIVITY ON A BLOCK-FACE (T 3.18)	<p>Negative impact under this criterion from lack of access to parking; minor negative impact from lack of access to load zone.</p>	<p>Minor negative impact, as preferred customer access point is the load zone.</p>	<p>Minor negative impact. Frequent aggressive vehicle maneuvers may reduce the desirability of foot-trafficking a shopping district.</p>	<p>Minor negative impact. Excessive vehicle congestion & queuing may reduce the ease and desirability of traveling to a shopping district.</p>	<p>Our metrics can capture minor-to-moderate changes in the extent of impacts to customer access.</p>

(4) Scenarios

This chapter (4) develops and depicts three scenarios: **(i)** an “existing” scenario, which is based on the existing curb space allocation on the block of Boren Ave N between John St and Thomas St in the City of Seattle, Washington; **(ii)** a “conversion” scenario, where much of the allocation provided for on-street public parking is converted to load zones; and **(iii)** a “flexibility” scenario, where much of the exclusive allocations provided (both public parking and load-zones) are converted to permit both uses. The following section 4.1 lists the parameters which were held constant across modeling each scenario, as well as the standards assumed for reporting results. Scenarios are presented in sections 4.2.

4.1 - Control parameters & standard procedures

Several model parameters were held constant throughout modeling of each intervention scenario. These parameters can be grouped into two categories: **(i)** parameters held constant to roughly reflect study observations drawn from the literature; and **(ii)**, parameters held constant because altering them would have a direct and significant effect on the results of the model, but would not reflect a policy intervention that might occasion such an effect.

The first group of parameters was:

a. AM / PM-period demand patterns — as referenced above in section 3.3, the proportion of TNC demand in each period reported by Goodchild & MacKenzie was roughly 88 drop-offs : 12 pick-ups during the AM peak, and 10 : 90 during the AM.

b. The chance of a private vehicle wanting to park — this is not an

observer interface parameter, but it is controlled by the ABM procedure for creating private vehicle agents (“create-private”). It was set to a value — ~33% — which produced a proportion (28-38%) of parking events : total loading events roughly equivalent to that reported by Fehr & Peers in the 2018 study in San Francisco for the Hayes St commercial corridor (37%) (p. 49).

The second group of parameters was:

- a. Ped-speed — Held constant at 0.035 for all model runs.
- b. Acceleration — Held constant at 0.008 for all model runs
- c. Deceleration — Held constant at 0.02 for all model runs.
- d. Max-vehicle-patience — Held constant at 15 for all model runs.
- e. Number-of-private — Held constant at 15 private vehicles agents
- f. Number-of-passengers — Held constant at 10 passenger & drop-off agents
- g. Number-of-parked — Held constant at 3 permanently parked cars
- h. Mean-pass-patience, SD-pass-patience, Min-pass-patience; Mean-wait-time and SD-wait-time — These values define the standard distributions used to determine each TNC passenger's “patience” parameter and the amount of time they “wait” for their TNC vehicle, as well as the minimum “patience” required to load at a load zone. These parameters thus reflect the ABM’s assumptions about passenger-agents’ decision-making priorities. They were held constant at values that kept loading demand close to the loading capacity

provided in the “existing” scenario. This approach kept almost all provided loading zones in regular use, with occasional vehicles unable to park or access a load zone, but without destabilizing the model. Mean-pass-patience, SD-pass-patience and min-pass patience were held constant at 320, 50, and 50, respectively; Mean-wait-time and SD-wait-time at 300 and 100.

The specific values used for the above parameters are somewhat arbitrary, but were developed through trial-and-error on the “Existing” scenario to find a set of values that kept agent behaviour legible while maintaining the model in a stable pattern.

i. Mean-park-time and SD-park-time — These values were set to 2700 and 900, respectively, to reflect two related assumptions. First, it was assumed that — although arbitrarily defined in terms of “ticks”, or model time-units — the “wait-” and “travel-time” mechanics set by the “mean-” and “SD-wait-time” parameters represent ~10 minute headways from the time a passenger requests a TNC pick-up. And second, it was assumed that average parking time would be approximately 90 minutes²², meaning about 9 * TNC headways ($9 * 300 = 2700$).²³

Alongside these parameters, a standard procedure was used for modeling the “existing” and the two intervention scenarios. For each scenario, the ABM was

²² This was the mean parking time observed on a “commercial corridor” in San Francisco by Fehr & Peers in the 2018 curbspace study.

²³ This frame of reference translates the maximum vehicle “patience” value (described above in sections 3.2 and 3.3) to ~30 seconds.

run 5 times under each commute period (AM / PM), with a runtime of 15,000 - 50,000 ticks (~ 3 - 9 mins at “faster” speed). Each intervention scenario was therefore modeled 10 times, split evenly between simulations of the AM and PM periods. A unique recording of each ABM run used for data collection was made using the MacOS application “Grab”.²⁴ The ABM was allowed to run without intervention from the researcher. If this resulted in the system becoming significantly unstable during a run, a screen recording of each type of destabilizing event was preserved, but quantitative results from after the point the model became unstable were discarded.

This resulted in an average of ~3,663 observations of loading events (including parking vehicles) across all model runs, with an average of ~1442 observations of TNC loading behaviour. A summary of the data collected is presented in Table 1 sections 5.1. Also presented in sections 5.2 and 5.3 is the data used to inform matrix evaluations of the each of the two modeled interventions (Table 2 & Table 3). The full set of data collected is provided in Appendix 1.

4.2 - Scenarios

Three scenarios were modeled. As mentioned above in section 3.1, in every modeled scenario, 3 immobile parked car agents are randomly placed in available parking spots at the outset. This is intended to represent any number of

²⁴ These recordings were preserved by the researcher and are freely available upon request. The size of the video files prevents including them as an appendix. Contact the researcher at: jackson dot koch at protonmail dot ch.

contingencies (freight activity; construction in the right-of-way; bus layover; immobilized vehicles; emergency service vehicles; etc.) which might occur to reduce the number of open load zones on a given day.

(i) The “existing” scenario — this should be considered the control scenario. It is roughly based on the existing curb-space allocation on the west block-face of Boren Ave between John St and Thomas St. It provides for 2 dedicated load-zones, one north and one south, and 14 parking spots, for a total of 16 loading areas (13 net the 3 randomly placed immobile cars). A representative set up is shown below (parking spaces are a lighter pink than load zones).

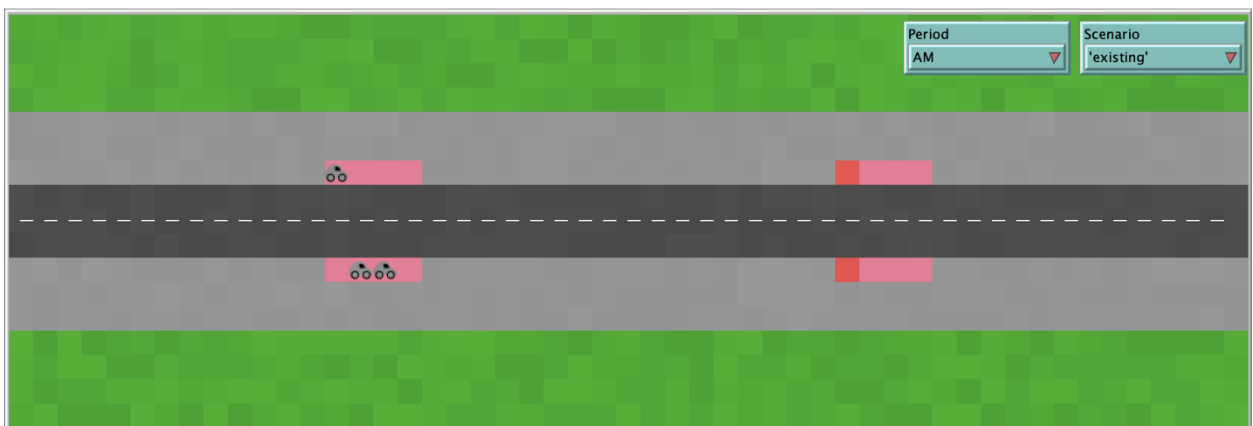


Image 3 - existing scenario

(ii) The “conversion” scenario — based on Fehr & Peers’ “conversion” recommendations for the Hayes St commercial corridor in San Francisco, this scenario converts two of the designated parking spaces to load zones. This leaves 4 dedicated load zones and 12 (9 net) parking spots. A representative set up is

shown below (parking spaces are a lighter pink than load zones).

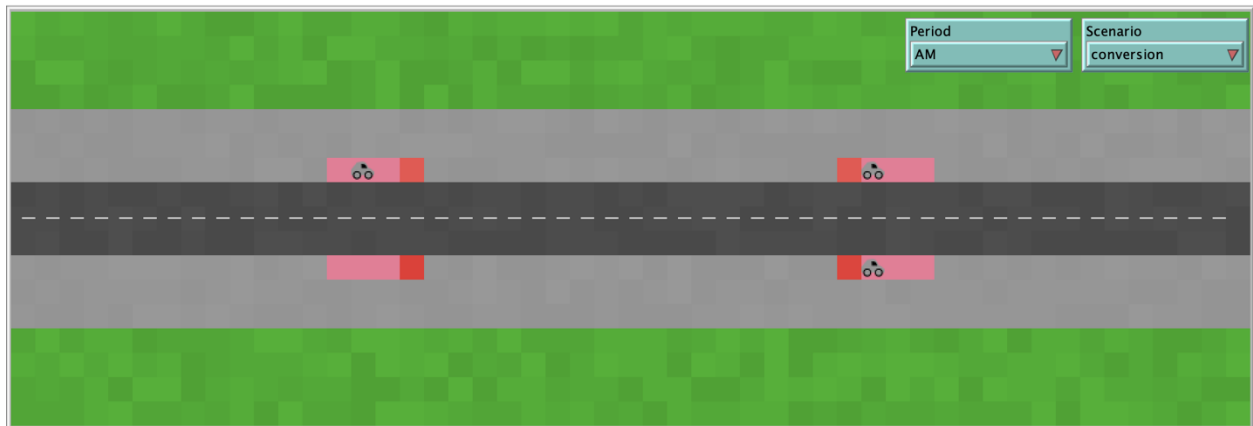


Image 4 - conversion scenario

(iii) The “flexibility” scenario — “Flexibility” as proposed by Fehr & Peers refers to dynamic management of curb space allocation, changing the uses permitted and prohibited throughout the day. The ABM developed for this study is not sophisticated enough to represent the time-of-day travel-pattern concepts that inform this intervention, so an alternate version of the intervention was developed that introduces flexibility simply between the AM- and PM-peak periods. In the AM period, two additional dedicated load zones are provided, as was the case in the “conversion” scenario. These load zones are coloured green in the model.

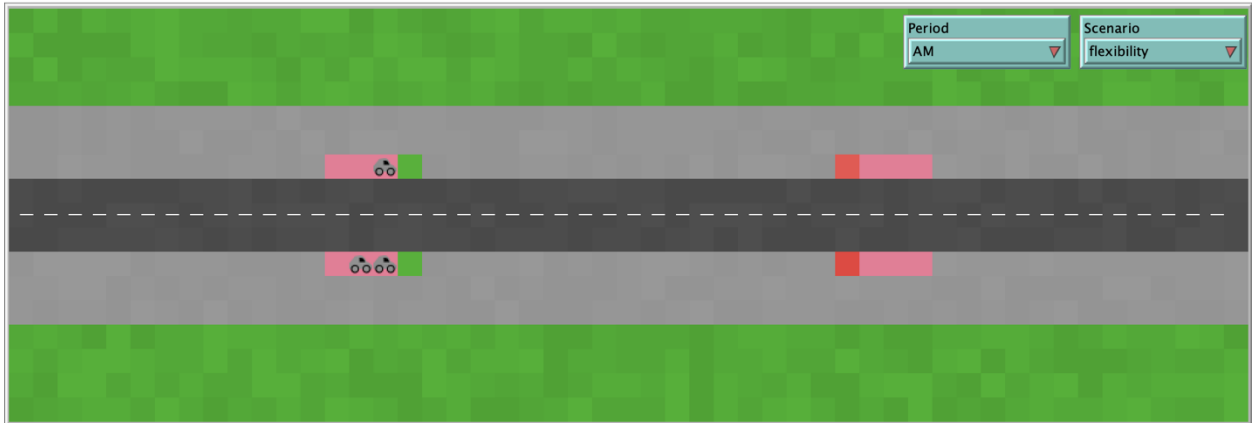


Image 5 - flexibility scenario AM

In the PM period, all dedicated load zones revert to public parking (which TNC agents will use for loading). These load zones are coloured green and blue in the model.

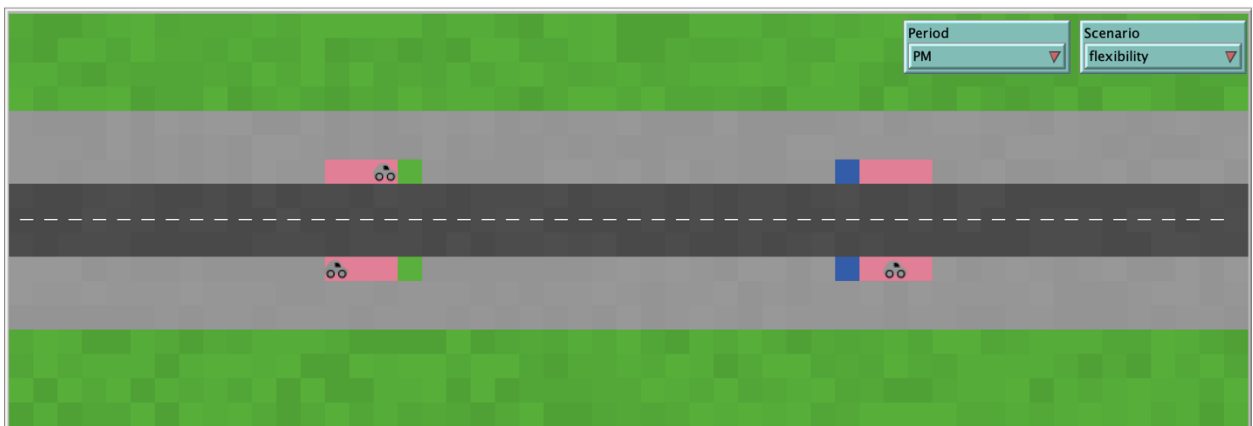


Image 6 - flexibility scenario PM

The “flexibility” intervention as modeled is thus too far from a straightforward representation of the intervention proposed by Fehr & Peers for a direct evaluation of their proposal. It is instead intended to allow evaluation

and investigation of a laissez-faire curb space regime, where both of the modeled modes can use all available curb space on a first-come, first-served basis.

The following chapter (5) presents the results of modeling these scenarios using our ABM both overall (section 5.1) and for each intervention (sections 5.2 & 5.3).

(5) Results & Evaluation

This chapter (5): **(i)** gives overall observations and inference drawn from the ABM as a whole; **(ii)** reports the results of modeling the “existing”, control scenario as well as **(iii)** the intervention scenarios; and reports the results for each intervention scenario together with **(iii)** a matrix evaluation of the outcomes.

The results for the “existing” scenario are found together with overall observations in section 5.1. The following sections 5.2 and 5.3 report results for the conversion and flexibility interventions respectively.

5.1 - Overall model results

This section presents overall statistics on the performance and stability of the ABM, together with observations about the model’s behaviour across all 30 runs used to inform this study and under the “existing” scenario. The following sections 5.2 and 5.3 present similar statistics and observations specific to each modeled intervention scenario. A complete table of statistics may also be found in Appendix 1.

	Total – existing	Total – conversion	Total – flexibility
In roadways	62.2% (2008)	63.5% (2735)	62.7% (2168)
At load zones	16.2% (524)	15.9% (683)	15.5% (535)
Successfully parked	21.6% (696)	20.5% (884)	21.9% (756)
All loading events	3228	4302	3459
Couldn't find parking	84	287	171
Couldn't find load zone	34	19	22
Passing time	25413	26500	22254
Ped passing time	21715	24875	18134
(Net) Vehicle passing time	3698	1625	4120
Queuing time	24506	35685	24560
Model uptime	259,277	369,546	282,434

Table 1 - Overall model summary

(i) *Statistics* — Across 30 ABM runs, the model was stable for an average of ~30,000 ticks (cycles). This generated a total of 10,989 observations of loading events (including public parking), and 8,653 observations of TNC agent loading events. The most stable scenario for these runs was the conversion intervention (~36,000 average cycles); the more stable period, in every scenario, was the AM-peak.

As expected, in-roadway TNC loading operations were more represented (6911 observations) than were operations at a load zone (1,742). However, the rate of in-roadway loading was also quite consistent across scenarios, which was not expected. TNC loading in a load zone as a share of all successful loading

events was 15.5 – 16% across each scenario. TNC agents attempted to load in a load zone during ~25 - 28% of all observed TNC loading operations. This proportion was highest in the “existing” scenario (27.79%) and lowest after the conversion intervention (25.69%). This suggests the rate of in-roadway / at load zone behaviour is too strongly controlled by the normal distribution used in assigning the “passenger-patience” of TNC drop-off and passenger pick-up agents to be affected by changes in the allocation of curb space. As discussed in the following sections, however, the number of agents unable to access a load zone did appear to respond to intervention, with the conversion intervention performing slightly stronger.

Vehicle behaviour also showed variance across scenarios, and particularly across time-periods. Passing time, pedestrian passing time, and vehicle queuing time each accounted for about ~8-10% more total model uptime in the PM scenario than the AM. Less variation was observed between scenarios, but the conversion intervention reported queuing or unsafe vehicle behaviour during the smallest portion of model uptime.

(ii) Observations — By far the most common cause of instability seen in the model was two vehicles attempting to access the same load zone at the same time, particularly if one of the two agents was attempting to cross a lane of traffic in order to park or perform loading at the curb. This pattern created numerous instances of (quite plausible) “fender-bender”-style traffic conflicts. The model does not reflect collisions, but the offending agents would frequently recognize

the oncoming car, halt, and thus become caught in a coordinate position for which the ABM does not specify procedures. This is a direct consequence of the means used to specify vehicle agent behaviour in the ABM — motion is prescribed based on the y- and x-coordinate positions that agents report (e.g., “if an agent’s y-coordinate = 1, move west”). It is also an indirect consequence of the need to restrict the amount of information the model passes to an agent — the ABM should not simply tell one of the agents that the other wants the parking spot — as well as of our mandate to avoid over-determining outcomes by hyper-specifying agent behaviour.

It was also observed that this particular pattern of behaviour capsizing the model was more likely to occur in the first 3 - 8,000 ticks of a model run. This appears to partly correspond to the patterns of arrival and departure of TNC agents, which (as in any commute period) have structural moments of beginning, peak, and tapering off. In this case, these moments appear to correspond to the shape of the normal distribution used to assign “travel-” and “wait-time”. The random chance of the ABM spawning a private vehicle agent is consistent (1%) at any given model cycle. If a number of these spawns occur both in (near-) succession to each other and during the peak of the model's "commute period", it is more likely that vehicles will find themselves competing for the same stretch of curb at the same time.

In a similar vein, an intriguing consequence of the model's use of normal distributions was the interaction between “park-time” and “wait-/travel-time”. If the model was able to get through the initial normally-distributed commute

cycle, the difference between the parking time and travel time distributions can create overlapping patterns of behaviour. A private vehicle that parked during the beginning of the initial commute period would often still be parked when the second commute period reached the its peak or concluding moment, which prevents other vehicles from parking or using the load zone and thereby alters the traffic pattern. The consequences of this overlap in turn mean the number of available parking spaces and load zones at one point in the third commute cycle were often distinct from that same point in the first and the second commute cycles.

(iii) *“Existing” scenario* — Despite the observed variance in the availability of curb space over the course of a model run, TNC vehicle and passenger agents were able to find an empty parking or load zone for almost all loading events in the “existing” scenario. Table 2 below shows the results observed.

Scenario	"Existing"			Share of total AM loading events	Share of total PM loading events	Share of total loading events
	AM	PM	Total			
In roadways	1083	925	2008	57.79%	68.32%	62.21%
At load zones	377	147	524	20.12%	10.86%	16.23%
Successfully parked	414	282	696	22.09%	20.83%	21.56%
All loading events	1874	1354	3228	58.05%	41.95%	
Couldn't find parking	53	31	84	2.83%	2.29%	2.60%
Couldn't find load zone	17	17	34	0.91%	1.26%	1.05%
				Share of total AM uptime	Share of total PM uptime	Share of total uptime
Passing time	9636	15777	25413	6.57%	14.02%	9.80%
Ped passing time	6468	15247	21715	4.41%	13.55%	8.38%
(Net) Vehicle passing time	3168	530	3698	2.16%	0.47%	1.43%
Queuing time	7839	16667	24506	5.34%	14.81%	9.45%
Model uptime	146,763	112,514	259,277			

Table 2 - "Existing" scenario outputs

Model headlines — 10 ABM runs generated ~259,000 cycles of stable uptime for a total of 3228 successful loading events, 2532 TNC-related. 34 of these TNC-related loading events (~1.34%) occurred in the roadway because an agent was unable to access a load zone. An additional 84 vehicles were unable to find parking (~10.77% of total parking & failure to park events).

Loading events — Lack of access to a load zone was split evenly between periods, while lack of access to parking was somewhat concentrated (63%) in the AM-period. This latter appears to be due to a higher (+~9.5%) proportion of loading events occurring at the curb during the AM period. The higher number of at load zone loading operations in the AM period increases the chance that a private vehicle traveling the block will find all parking spaces occupied.

This intuition may need to become more complicated, however, to account for the result that a higher proportion of TNC-related loading events were reported unable to access a load zone during simulations of the PM period. The proportion of PM period TNC / passenger agents that wish to load at a load zone (164), relative to the total number of PM period TNC / passenger agent-related loading events (1089), is ~15%; the equivalent in the AM period was ~25%. It would seem counter-intuitive that the period producing a ~11% lesser proportion of TNC / passenger agents wishing to load at load zones also produces ~0.35% more instances of passengers unable to access a load zone. All things being equal, one would expect less demand to produce a higher proportion of demand being served.

But observation of the data recordings suggests that considering this point can help clarify the different natures of the two forms of TNC loading activity (drop-off and pick-up) in the ABM. TNC vehicles for drop-off proceed down the roadway until reaching either a free load zone (if their passenger is still “patient”) or until they are roughly parallel to the “building entrance” (center of the map). When they reach their passenger’s preferred destination, the passenger alights. TNC vehicles for pick-up, however, proceed down the roadway until they “see” their passenger. When they see the passenger, a series of decisions are made based on how close they are to the passenger and whether there is an open load zone, and whether the passenger steps off the curb into the roadway. This means there is more space in the pick-up behaviours for an organic decision — the passenger was still “patient”, but, they turned their head and saw their Lyft approaching, and began walking towards it without thinking. This, in turn, reduces the number of loading operations that occur at a load zone, but without increasing the number of passengers who *wanted* to access a load zone, but couldn’t. Finally, this (potentially) organic reduction in the rate of loading at a load zone can explain why private vehicles have less trouble parking in the PM period.²⁵

²⁵ The pattern described also accords with Goodchild & MacKenzie’s finding that on-street loading is 4% more common for pick-ups than drop-offs. I am grateful to Prof MacKenzie for initially describing this pattern.

5.2 - Conversion scenario results

Table 3 on the following page reports output totals for the 10 ABM runs under the conversion intervention scenario. A list of the categories of impacts captured is also reproduced here for ease of reference:

- (i) vehicles unable to access a parking space / load zone;
- (ii) the rate and number of loading operations occurring in the roadway
- (iii) unsafe vehicle passing maneuvers (passing both pedestrians and other vehicles)
- (iv) number of vehicles observed queuing / idling behind an idling TNC vehicle.

Scenario	Conversion			Share of total AM loading events	Share of total PM loading events	Share of total loading events
	AM	PM	Total			
In roadways	1694	1041	2735	60.39%	69.54%	63.58%
At load zones	554	129	683	19.75%	8.62%	15.88%
Successfully parked	557	327	884	19.86%	21.84%	20.55%
All loading events	2805	1497	4302	65.20%	34.80%	
Couldn't find parking	185	102	287	6.60%	6.81%	6.67%
Couldn't find load zone	3	16	19	0.11%	1.07%	0.44%
				Share of total AM uptime	Share of total PM uptime	Share of total uptime
Passing time	7896	18604	26500	3.43%	13.38%	7.17%
Ped passing time	7137	17738	24875	3.10%	12.76%	6.73%
(Net) Vehicle passing time	759	866	1625	0.33%	0.62%	0.44%
Queuing time	12523	23162	35685	5.43%	16.66%	9.66%
Model uptime	230,522	139,024	369,546			

Table 3 - Conversion scenario outputs

Model headlines — 10 ABM runs generated ~369,500 cycles of stable uptime for a total of 4302 successful loading events, 3,418 TNC-related. 19 of these TNC-related loading events (~0.56%) occurred in the roadway because an agent was unable to access a load zone. An additional 287 vehicles were unable to find parking (~24.5% of total demand for parking).

Loading events — The intervention doubled the supply of dedicated load zones in both the AM and PM peak periods, and generated a ~0.78 overall percentage point reduction in agents unable to find a load zone. This represents a ~58% reduction in failed at load zone loading, with ~80% of the reduction concentrated in the AM period. The intervention therefore clearly appears to have some effect. It did not, however, meaningfully alter the proportion of total loading events in the roadway, whether TNC-related only or TNC-related and otherwise. As discussed above in section 5.1, it is not clear that this reflects a failure on the part of the intervention. On the one hand, passengers wanting to load at a load zone are so infrequently blocked from doing so that it would be impossible to meaningfully affect the rate of loading in the roadway solely by changing their loading outcomes. But on the other hand, loading in the roadway was observed at such a consistent rate across all modeled periods and scenarios that it seems equally plausible for the failure to observe a change to be the result of specifying

the ABM with a constant value for “min-pass-patience”.²⁶

Finally, the proportion of unmet demand for public parking increased by almost 15 percentage points, a more than 100% increase. This is a clear impact, and is discussed further in the evaluation matrix below (after vehicle behaviours).

Vehicle behaviours — As one can see from Tables 2 & 3, passing time and pedestrian passing time’s share of total model uptime both shrank from the “existing” to conversion scenario, while queuing time remained stable.²⁷ The latter suggests that the failure to reduce the rate of TNC loading operations performed in-roadway preserved the knock-on effects of TNC idling on other traffic. The former, however, appears to indicate that the system was “safer” under the conversion scenario, as the amount of unsafe vehicle maneuvers around pedestrians shrank by ~2.6 percentage points (and the amount of unsafe vehicle passes in the center of the roadway by ~1.6 percentage points).

Improvement in these safety metrics was again concentrated in the AM period. There are at least two plausible explanations for this observation. First, the number of vehicles unable to park did not only reduce in absolute terms. Parking’s share of total loading events also decreased by ~2 percentage points in

²⁶ It would be valuable in this context to perform an alternate ABM series where “min-pass-patience”, like “wait-” and “travel-time”, is normally distributed, instead of fixed.

²⁷ It is important to recall here (from section 3.3) that these figures do not necessarily indicate the total quantity of unique model cycles during which an agent was queuing. This is, first, because any instance in which multiple agents queue behind an idling vehicle generates (1) queue time for *each* idling vehicle (so multiple queue times can be generated for one model cycle). And second, because agents also add (1) to queue time whenever they slow down (but do not idle) due to a slower agent ahead. Metrics are related to their share of total model uptime in order to relativize them across model runs.

the AM period (~1 point overall). The reduced number of vehicles attempting parking maneuvers could mean fewer conflicts between vehicles entering / exiting a parking spot / travel lane, or between a vehicle entering / exiting a parking spot and a passenger attempting to walk off the curb. Second, it is possible that, although the additional loading zones did not increase the rate of loading at a load zone, they did increase both the ease with which TNC and passenger agents are able to access a dedicated load zone and the rate at which loading occurred in a *dedicated* load zone (i.e., not in a parking spot). It seems plausible that providing additional curb space where loading can occur but private vehicles are unable to park would reduce the potential for conflicts between those using the load zone and private vehicles attempting to park.

Evaluation — conversion

The evaluation matrix for the conversion intervention is found on the following page. A list of the evaluative criteria developed from *CoS 2035* is also reproduced here for ease of reference:

- (i) increased the number of drop-offs on a block-face in a retail district (“customer access”)
- (ii) decreased the number of in-street drop-offs on a block-face where current curb-space allocation conflicts with efficiently serving the predominant modal activity
- (iii) the potential for conflicts between two vehicles and between vehicles and pedestrians
- (iv) conflicts with the land-use context or plans for modal infrastructure
- (v) if it unduly raises the competitiveness of one mode where modal planning had intended the priority of another.

Metrics

Criteria

	VEHICLES UNABLE TO ACCESS PARKING SPACE / LOAD ZONE	RATE & NUMBER OF LOADING OPERATIONS OCCURING IN THE ROADWAY	UNSAFE VEHICLE MANEUVERS	VEHICLES QUEUING / IDLING BEHIND A SLOWER VEHICLE	SUMMARY
COMPETITIVENESS OF THE TNC MODE FOR MODE SHARE (T 2.2; T 2.5)	TNC vehicles' ability to access a load zone when desired increased by 58% over the "existing" scenario. Minor positive impact to competitiveness of the TNC mode. Private vehicles ability to access parking was decreased by 150%. Positive impact to competitiveness of the TNC mode.	<i>Negligible impacts observed, as the rate of TNC loading in the roadway did not meaningfully change.</i>	Minor positive impact from 1 percentage point reduction in vehicle-vehicle passing maneuvers. Positive impact from 2 percentage point reduction in maneuvers in the presence of a more vulnerable user.	Negligible impact to the competitiveness of the TNC mode, as queuing time changed less than a quarter of a percentage point.	The conversion intervention had significant positive impacts on the competitiveness of the TNC mode, due to improvements to safety, access to curb space, and the deterioration of conditions for private vehicles seeking on-street parking.
MISALIGNMENT BETWEEN ALLOCATION AND PREDOMINANT USE (T 3.18)	Negative impact due to significant amount (25%) of demand for public parking unmet.		N/A		The intervention had significant negative impacts due to significant unmet demand for public parking. However, all other metrics unchanged for this criterion.
POTENTIAL FOR CONFLICTS (TG 2; T 2.3; T 2.5)	<i>Negligible impacts observed, as the rate of TNC loading in the roadway did not change.</i>		Positive impact from overall reductions in unsafe vehicle maneuvers	<i>No impact relative to the "existing" scenario.</i>	Positive impact from reductions in overall unsafe vehicle maneuvers. However, all other metrics unchanged for this criterion.
CUSTOMER ACCESS & ACTIVITY ON A BLOCK-FACE (T 3.18)	Negative impact due to significant reduction in parking access. Minor positive impact due to increased ability of TNC passengers to access load zone.		Minor positive impact due to reduction in unsafe vehicle maneuvers in the presence of pedestrians.		Negative impacts due to significant reduction in parking access. However, minor positive impacts due to increased access to load zones and reduction in unsafe vehicle behaviour.

Safety metrics were meaningfully improved for all users under the conversion intervention scenario. However, outside the safety metrics, the intervention produced clear winners and losers in the evaluation matrix. Unmet demand for public parking spiked 150%, indicating a mis-alignment between the modeled traffic patterns and available curb space. Significant negative impacts on customer access & activity on the block-face were also identified.

Given the real improvements in safety and access to load zones, there are clear use cases for this intervention. Blocks that see a significant number of conflicts involving TNC vehicles loading in the roadway are clear opportunities, as are blocks with a higher average number of drop-offs than pick-ups. But the impacts on public parking mean blocks with a number of ground-floor businesses dependent on public parking will be less likely candidates. This suggests the strongest use case for the conversion scenario will be a downtown office block, where retail is more often dependent on foot traffic and there is greater access to off-street public parking. Blocks in the vicinity of special event facilities, where vulnerable users are more likely to be in the roadway and on-street parking is inevitably insufficient to meet demand, are also strong options.

Given that the intervention was not, however, observed to reduce vehicle queuing time or the rate of in-street loading activity, the case for this intervention does not appear strong on corridors planned for public transit access. This is doubly true as the intervention appears to increase the competitiveness of the TNC mode even without increasing the queuing time of other vehicles. As the

improvement in TNC access to curb space was mostly concentrated in the AM period, blocks in night-life districts where pick-up activity is more prominent appear to be another, weaker, use case, although in this instance the lack of improvement in curb space access and impacts to public parking may be sufficiently offset by the improvements in safety around potentially inebriated pedestrians.

It should finally be noted that the significant increase in unmet public parking demand could have effects on public revenue from paid parking. Given the benefits seen in safety metrics, this may not be an unreasonable trade-off. But it may make the intervention less desirable in contexts where vehicle conflicts are not already a significant concern.

5.3 - Flexibility scenario results

The following Table 4 reports output totals for the 10 ABM runs under the flexibility intervention scenario.

Scenario	Flexibility			Share of total AM loading events	Share of total PM loading events	Share of total loading events
	Period	AM	PM	Total		
In roadways	1337	831	2168	59.82%	67.89%	62.68%
At load zones	428	107	535	19.15%	8.74%	15.47%
Successfully parked	470	286	756	21.03%	23.37%	21.86%
All loading events	2235	1224	3459	64.61%	35.39%	
Couldn't find parking	154	17	171	6.89%	1.39%	4.94%
Couldn't find load zone	1	21	22	0.04%	1.72%	0.64%
				Share of total AM uptime	Share of total PM uptime	Share of total uptime
Passing time	6853	15401	22254	3.77%	15.29%	7.88%
Ped passing time	6470	11664	18134	3.56%	11.58%	6.42%
(Net) Vehicle passing time	383	3737	4120	0.21%	3.71%	1.46%
Queuing time	10780	13780	24560	5.93%	13.68%	8.70%
Model uptime	181,737	100,697	282,434			

Table 4 - Flexibility scenario outputs

Model headlines — 10 ABM runs generated ~282,434 cycles of stable uptime for a total of 3459 successful loading events, 2,703 TNC-related. 22 of these TNC-related loading events (~0.81%) occurred in the roadway because an agent was unable to access a load zone, all but one of them in the PM (*laissez-faire*) period. An additional 171 vehicles were unable to find parking (~18% of total demand for parking), 154 of them in the AM (2 additional dedicated load zones) period.

Loading events — The intervention doubled the supply of dedicated load zones in the AM period, then opened all curb space to all users in the PM. This generated a ~0.53 overall percentage point reduction in agents unable to find a load zone, but this gain was entirely made in the AM period. The PM period saw a ~0.65 percentage point increase in the number of TNC / passenger agents unable to locate a load zone, equivalent to a ~41% increase.

Parking events saw an inverse pattern. Unmet parking demand in the AM period increased by 7.23 percentage points, an ~67% increase. In the PM period, public parking flourished, producing only 17 instances of unmet demand. This is an almost 50% improvement over even the PM existing scenario, which reported 31 instances. The increased supply of public parking also clearly explains the negative impacts on the ability of TNC / passenger agents to find a load zone in the PM period.

It seems unlikely, however, that these patterns of impact are the consequence of the AM / PM period change. The AM flexibility scenario is equivalent to the AM conversion scenario, and reports outputs that are roughly in line with the

same. The changes in rates of impact to loading behaviour which are distinct in the PM period are more plausibly explained by the laissez-faire curb space regime, and its interaction with the tendency of parking vehicles to park for extended periods of model uptime, than to anything specific to PM period behaviour.

The intervention therefore clearly appears to have some effect. But it once again did not meaningfully alter the proportion of total loading events in the roadway, whether TNC-related only or TNC-related and otherwise. The rate remained in the consistently observed range of ~60% of all loading behaviour in the AM period, and ~68% in the PM (~63% total).

Vehicle behaviours — Relative to the “existing” scenario, the flexibility intervention reduced passing time and ped passing time’s share of model uptime by ~2 percentage points. These improvements appear comparable to those observed in the conversion scenario (although ped passing did improve by an additional ~0.41 percentage points over conversion).

But flexibility did differ from conversion more meaningfully under the remaining vehicle behaviour metrics. Vehicle passing time — reported when a private vehicle passes a car or passenger agent by traveling in the center turn lane — increased by 1 percentage point relative to conversion, driven entirely by an increase of nearly 3 percentage points in the PM period. This puts it within .03 of the vehicle passing time reported for the “existing” scenario. Inversely, queuing time under flexibility decreased by ~1 percentage point from the

conversion scenario, although in this latter case it was equally an improvement over “existing”. But the improvement in queuing time over conversion was again driven by a 3 (2 over “existing”) percentage point improvement in the PM period specifically.

Each of these changes on its own could point to model noise, and that remains a plausible explanation. But, because the latter metric is not a *negative* outlier (i.e., because flexibility did not degrade, but rather improved, queuing), it seems unlikely to have been caused by an unnoticed destabilizing event in an ABM run(s) used for data collection. The destabilizing events which were observed uniformly served to degrade the performance of queuing time as vehicles endlessly idled behind an immobilized vehicle. A stronger explanation might focus instead on the concentration of these changes in the PM period. TNC vehicles accessing load zones may generate queuing time as vehicles traveling behind them wait for them to safely navigate out of or back into the travel lane. If increased competition for load zones relative to “existing” pushed marginally more loading into the roadway (and the rate of PM “existing” in-roadway loading was 2.3 percentage points lower than that of PM flexibility in-roadway loading), it could thereby generate marginally less queuing.²⁸

²⁸ It could also be the case that the increased provision of public parking during this period reduced opportunities for queuing behind conflicts between vehicles vying for “the last parking spot”, although this explanation might require a concomitant rise in the rates of other types of conflict in order to account for the fact that overall passing time remained within ~0.6 percentage points of that reported under the conversion scenario.

	VEHICLES UNABLE TO ACCESS PARKING SPACE / LOAD ZONE	RATE & NUMBER OF LOADING OPERATIONS OCCURING IN THE ROADWAY	UNSAFE VEHICLE MANEUVERS	VEHICLES QUEUING / IDLING BEHIND A SLOWER VEHICLE	SUMMARY	
Criteria	COMPETITIVENESS OF THE TNC MODE FOR MODE SHARE (T 2.2; T 2.5)	Minor positive impacts in the AM period due to blocked demand for public parking; minor negative impacts in the PM due to decrease in access to load zones by TNCs.		Minor negative impacts relative to conversion due to an increase in vehicle passing; positive impacts relative to “existing” scenario due to improvement in all safety metrics but vehicle passing.	Minor positive impacts in the PM due to 1 percentage point increase relative to existing scenario; to be confirmed with additional data collection.	Minor benefits to competitiveness of TNC mode in the AM period due to difficulty accessing public parking, and positive impacts due to improvements in some safety metrics. Improvement in PM queuing times negated by decreased PM period access to load zones.
	MISALIGNMENT BETWEEN ALLOCATION AND PREDOMINANT USE (T 3.18)	Negative impacts to public parking in the AM; minor positive impacts to public parking in the PM period.		N/A	Minor positive impacts in the PM due to 1 percentage point increase relative to existing scenario; to be confirmed with additional data collection.	Signs of meaningful misalignment between use and allocation in the AM period, but this is arguably a policy goal under flexibility. Minor positive impacts in the PM period.
	POTENTIAL FOR CONFLICTS (TG 2; T 2.3; T 2.5)	Minor positive impacts in the AM period; minor negative impacts in the PM, due to pattern of load zone accessibility.	Negligible impacts observed, as the rate of TNC loading in the roadway did not meaningfully change.	Positive impacts relative to the “existing” scenario due to reductions in most safety metrics; minor negative impacts relative to the conversion scenario due to 1 percentage point increase in vehicle passing time.	No impact	Positive impacts, with additional in the AM period, relative to the “existing” scenario, but minor negative impacts in the PM period and relative to conversion due to increased vehicle passing.
	CUSTOMER ACCESS & ACTIVITY ON A BLOCK-FACE (T 3.18)	Negative impact under this criterion from lack of access to parking in the AM; minor negative impacts in the PM relative to total TNC loading activity.		Minor positive impacts relative to the “existing” scenario; no meaningful change relative to the conversion scenario.	Minor positive impacts in the PM due to 1 percentage point increase relative to “existing” scenario; to be confirmed with additional data collection.	Negative impact to customer accessibility via public parking in the AM, and minor negative impacts to accessibility via TNC in the PM, but both of these are arguably policy goals under flexibility. Additional minor benefits relative to “existing” scenario in the PM period from safety and queuing improvements, to be confirmed with additional data collection.

A strong use case for the flexibility intervention studied here will be a land use context that drives travel patterns which are variable over the course of the day, but predictably so. The AM-peak pattern could be commute focused, but if the policy maker adopts goals similar to those developed above from *CoS 2035*, many contexts with an AM commute pattern (like the downtown office core) will be better candidates for the conversion intervention. This mismatch is partly because of the incentives for public parking which the flexibility intervention introduces in the PM peak, and which could in turn drive single-occupancy vehicle trips downtown. It is also because of the more limited nature of the flexibility intervention's improvements to our vehicle-vehicle safety metrics — particularly in the PM peak — relative to the conversion intervention's performance. This may make lower volume, neighbourhood commercial arterials a stronger use case for flexibility, given the intervention showed a marginally stronger performance on our pedestrian-vehicle safety metrics than did conversion. This “quiet in the morning, lively in the evening” context would also allow the policymaker to lessen the negative impacts of AM flexibility on public parking. Matching the strengths and benefits of the intervention in each period to the existing land use pattern in the intervention site is a straightforward way to identify strong use cases.

However, a similar, inverted, use case for the flexibility intervention we studied may be one where public parking and TNC activity are inevitably competing for curb space in the AM and PM periods. In such instances, a

policy maker may have reason to try to alter modal preferences in order to favour one or the other mode. An arterial slated for bus rapid-transit development with a pre-existing pattern of TNC drop-offs delaying traffic in the PM could be an example. The policy maker could implement the flexibility regime with the intention to reduce (at the margins) the attractiveness of TNC service along the corridor. The flexibility intervention could thereby introduce the observed fringe benefit of marginally reducing traffic queuing time. A similar use case could be found where a policy maker wishes to disincentivize public parking in the AM period.

If 24-hour conversion is unattractive or untenable, the policy maker will still have to evaluate between an “existing” style block-face allocation and the flexibility intervention. If the area sited for possible intervention has a pre-existing pattern of TNC activity in the PM period, the policy maker will have to balance the need for additional AM load zone capacity with the PM period impact on TNC curbside access. The same will be true for impacts to public parking in the AM.

This kind of balancing quickly suggests the value of a more dynamic flexibility intervention envisioned by Fehr & Peers, but that style of flexibility intervention also has drawbacks. As their report notes, dynamic curbside management above the level of posted signage designating specific uses for specific times of day introduces a need for specialized equipment (like geofencing and electronic signage) or employed personnel (like parking officers) that are often impractical for a given jurisdiction. In such instances where TNC

activity is prominent but governmental resources are limited, a more basic AM / PM flexibility intervention may show benefits.

This concludes the discussion and evaluation of results. Chapter (6) below presents possible directions in which this research could be extended, followed by conclusions.

(6) Conclusions & future analysis

6.1 - Directions for future research

There are two broad directions in which this research could be extended: developing the capabilities of the ABM, and growing the policy context in which the evaluation occurs. Additional stability and more complex agent classes or behaviours would expand the capacity of the ABM to model scenarios resembling an existing transportation context. Closer specification to empirical parameters from the “real” world would enhance the model’s explanatory power. If the ABM was developed enough to reflect them, the evaluation’s policy context could be broadened to include empirical findings about travel mode impacts and traveler modal preferences from the literature. Outside of relation to the ABM, the policy context could also be deepened, to better respond to the particulars of a specific political context (whether it be the City of Seattle or elsewhere). Suggestions for each direction follow.

(i) *Development of the ABM* — The most immediate returns would likely be realized by development of the ABM’s procedures for vehicle following distance and yielding. The current model generally represents vehicle follow and yield behaviour as a simple calculation to stay at least 1 distance unit away from

leading / oncoming vehicles. This study was not able to incorporate existing research on driver following behaviour, but it is likely a more robust approach to these procedures would prevent the kind of “fender-bender” incidents that frequently destabilize the current model. This would be helpful for data collection, but it could also increase the value of the “Queuing” metric, given that “Queuing” is reported when procedures for vehicle following behaviour direct an agent to idle or slow down.

The ABM could also be expanded to reflect additional modal behaviour like freight or public transit. Freight vehicles would likely be easier to implement, as they could be developed as a variant of existing parking behaviour for private vehicle agents. A separate normal distribution for freight “unloading” time would likely produce the same kind of organic interactions with other modes as were observed in this study between private vehicle parking and TNC loading behaviour. It would also more accurately reflect the reality of demand for urban load zones. Transit would be more complex to implement, both because the size of the vehicle poses a greater threat to the stability of the model and because the relevant procedures would also require implementing a level of street infrastructure (e.g., bus stops) that was not considered for this study. It is also possible that implementing a public transit class of agent would require expanding the unit of analysis to multiple block faces, in order to maintain the stability of the traffic pattern.

The empirical specificity of the model could be deepened to more accurately reflect the existing pattern on a given street segment. If carried far enough

(dimensions; average turning radii), this could be used to implement and evaluate concepts like the speed with which vehicles can turn into a load zone, which would allow for an evaluation of the first intervention (relocation) proposed by Fehr & Peers. The model could also be specified with empirical observation of travel patterns over the course of whole days. This would allow for a more direct representation and evaluation of Fehr & Peers' "flexibility" intervention, where curb space allocation changes dynamically to reflect observed travel patterns. It would be valuable (for instance) to see how extreme a variation from observed travel patterns a dynamic allocation regime could handle before breaking down.

(ii) *Growing the policy context* — A clear limitation of the current ABM is the sole reliance on the normally-distributed "patience" metric to drive passenger and TNC agent preference for in-roadway or at load zone boarding / alighting. The current approach does have virtues, in that it succeeded in generating organic patterns by overlapping this distribution with that of private vehicle's parking time. But the resulting system preserves a rigidity in TNC and passenger agent decision-making that plausibly prevented one of our key metrics — the rate and frequency of in-roadway loading operations — from reporting meaningful change.

This focus on "patience" is equally a limitation of the policy context adopted to inform the model and subsequent evaluation. A more robust integration of stated-choice studies on modal behaviour in the ABM's assumptions would

strengthen our discussion of the impacts of each intervention on modal preference and behaviour in the policy evaluation. It would also allow us to specify, model and evaluate policy interventions more directly targeted at modal choice and agent behaviour. And — given that modal choice is often, to some extent, a consideration in an agent’s political decision-making — an ABM that took greater account of the drivers of modal preference could inform an additional discussion on the political viability of specific interventions. Intervention could be evaluated based on a balance of criteria between effect on an agent’s modal behaviour and the agent’s perception of the intervention itself.²⁹

This dimension of political visibility and viability connects also to the potential value of a stakeholder study when an agency in a specific political context is considering a determinate intervention. Links between the impacts of intervention on modal choice and behaviour and impacts on specific political constituencies would give a decision-maker a valuable sense of the likelihood a specific intervention can be politically feasible. This value could equally be developed at an abstract level, using a similar evaluative matrix to our own to structure a formal understanding of the relationship between classes of constituencies and classes of impacts. Such a matrix could in turn be linked back to the ABM by connecting classes of constituencies to classes of agents specified to share the former’s modal preferences and perceptions.

²⁹ As is often considered in so-called “nudge” interventions.

6.2 - Conclusion

TNC agents in our ABM are programmed to wait a random interval (up to 150 cycles) after loading operations at a load zone have completed. But the speed with which loading occurs meant it was quite rare in any of our model runs for all available load zones to be simultaneously occupied — even under the “existing” scenario. Only the PM-peak period of the flexibility scenario, wherein all users have first-come, first-serve access to all available curb space, were all load zones observed blocked for a meaningful period of stable model uptime.

This does not mean the interventions proposed by Fehr & Peers and evaluated in this study are not effective, or even that our ABM shows them not to be. The observations collected from the ABM clearly indicate that the evaluated interventions — conversion, in particular — are effective. But it does raise two related, if divergent, sets of questions.

First, to what extent does the lack of empirical specification in our model inevitably hamper its ability to reflect our research problem? If the dimensions, speed and turning capabilities of all agents were specified accurately in the model to a specific “real”-world scenario; or if passenger and TNC agents were given a more dynamic set of priorities when deciding whether to load in the roadway than our “patience” mechanic, would the rate of individuals unable to access curb space increase? Would the model thereby reveal a greater demand among TNC passengers for curb space than we have shown?

Second, to what extent is this a recurring problem in the “real” world? Our model, which allowed up to 10 simultaneous TNC / passenger agents, and 15 simultaneous private vehicle agents, to vie for 13 patches of open curb space, generated an overall 25 - 28% rate of desire for TNC / passenger loading at the curb. But, in the ABM run with the highest proportion of total loading events where a TNC / passenger agent was unable to access a load zone, failed loading events were 2.52% of total loading & parking events, and 3.23% of total TNC loading. How often do TNC passengers or drivers actively wish to conduct loading operations in a parking space or load zone at the curb, but find themselves unable to do so? Is the rate of in-roadway loading operations a problem from the perspective of the individuals who use the mode, the passengers and drivers employed by TNC services? Or is it a largely — and it would not be less valid for being so — a problem from the perspective of policy makers and TNC service providers? And in the latter case, is it a problem for policy makers and TNC service providers that it is not a problem for drivers and passengers? The answer here will be as relevant to the nature of the policy interventions needed as is the efficacy of intervention itself.

References

- Aarhaug & Olsen (2018), "Implications of ride-sourcing and self-driving vehicles on the need for regulation in unscheduled passenger transport", *Research in Transportation Economics*.
- Adolph, Carolyn (2018), "Your Uber ride is partly why Seattle traffic got so bad", *KUOW*. Published online at:
<https://www.kuow.org/stories/your-uber-ride-partly-why-seattle-traffic-got-so-bad>
- Amirgholy & Gonzales (2015), "Demand responsive transit systems with time-dependent demand", *Transportation Research Part B*.
- Alemi et. al. (2018), "Exploring the latent constructs behind the use of ridehailing in California", *Journal of Choice Modelling*.
- Beekman, Daniel (2019), "Seattle drafted a plan to tax Uber and Lyft traffic months ago. Now what?", *The Seattle Times*. Digital edition March 22, 2019, accessed online at:
<https://www.seattletimes.com/seattle-news/politics/will-seattle-tax-uber-and-lyft-city-officials-have-been-thinking-about-it/>
- Bellafonte, Ginia (2018), "A Driver's Suicide Reveals the Dark Side of the Gig Economy", *The New York Times*. Digital edition, February 6, 2018, accessed online at:
<https://www.nytimes.com/2018/02/06/nyregion/livery-driver-taxi-uber.html>
- Castiglione et. al. (2017), "TNCs today: a profile of San Francisco transportation network company activity", San Francisco County Transportation Authority.
- Cramer & Krueger (2016), "Disruptive change in the taxi business: the case of Uber", *American Economic Review*, 106(5), 177–182.
- De Vos, Jonas (2018), "Do people travel with their preferred travel mode?", *Transportation Research Part A*.
- Fearnley et. al. (2018), "Competition and substitution between public transport modes", *Research in Transportation Economics*.

Fehr & Peers; ESA; Seattle Dept. of Transportation; Seattle Dept. of Construction and Inspections (2018), *Final Environmental Impact Statement: Seattle Center Arena Renovation Project*, Ch. 4 Transportation. Available online at: <http://www.seattle.gov/arena>

Fehr & Peers (2018), *Arena Access Management Plan (draft)*, prepared for Oak View Group. Available online at: <http://www.seattle.gov/arena>

Fehr & Peers (2018), "San Francisco Curb Study", prepared for Uber Technologies, rev. 1, Oct. 2018.

Finance & Administrative Services, City of Seattle (2014): "Operating Standards for TNC companies". Available online at: <https://www.seattle.gov/business-regulations/taxis-for-hires-and-tncs/transportation-network-companies/tnc-companies#operatingstandards>

Fitzsimmons, Emma G. (2018), "Uber Hit With Cap as New York City Takes Lead in Crackdown", *The New York Times*. Digital edition, August 8, 2018, accessed online at: <https://www.nytimes.com/2018/08/08/nyregion/uber-vote-city-council-cap.html>

Goodchild & MacKenzie (2019), "Curb Allocation Change Project: Interim Report", Urban Freight Lab at the College of Engineering, University of Washington (unpublished).

Henaio, Alejandro (2017), "Impacts of Ridesourcing –Lyft and Uber – on Transportation including VMT, Mode Replacement, Parking, and Travel Behavior," Doctoral Dissertation Defense.

Henaio & Marshall (2018), "The Impact of Ride-hailing on VMT", *Springer Nature*.

Ho et. al. (2018), "Potential uptake and willingness-to-pay for Mobility as a Service (Maas)", *Transportation Research Part A*.

KFH Group. (2008). *Guidebook for measuring, assessing, and improving performance of demand-response transportation*. Transit cooperative research program (Report No. 124). Washington, DC: Transportation Research Board.

- Mulley & Kronsell (2018), "The 'Uberisation' of public transport and mobility as a service (Maas)", *Research in Transportation Economics*.
- Office of Planning & Community Development, City of Seattle (2019): *Seattle 2035: City of Seattle Comprehensive Plan, Amended 2019*. Available online at: <http://www.seattle.gov/Documents/Departments/OPCD/OngoingInitiatives/SeattlesComprehensivePlan/CouncilAdopted2019.pdf>
- Salanova et. al. (2011), "A review of the modeling of taxi services". *Procedia Social and Behavioral Sciences* 20, 150-161.
- Salomon & Ben-Akiva (1983), "The use of the life-style concept in travel demand models", *Environment and Planning A*. 15, 623–638.
- Schaller, Bruce (2018), *The New Automobility: Uber, Lyft and the Future of American Cities*, Schaller Consulting.
- Wilensky, Uri (1997), "NetLogo Traffic Basic model". Center for Connected Learning and Computer-Based Modeling, Northwestern University. <http://ccl.northwestern.edu/netlogo/models/TrafficBasic>
- Wilensky, Uri (1999), NetLogo. Center for Connected Learning and Computer-Based Modeling, Northwestern University. <http://ccl.northwestern.edu/netlogo/>
- Wilensky, Uri & Payette, N. (1998), "NetLogo Traffic 2 Lanes model". Center for Connected Learning and Computer-Based Modeling, Northwestern University. <http://ccl.northwestern.edu/netlogo/models/Traffic2lanes>
- Wilensky, Uri & Rand, William (2015), "An Introduction to Agent-Based Modeling: Modeling Natural, Social and Engineered Complex Systems with NetLogo", MIT Press.
- Van Acker et. al. (2010), "When transport geography meets social psychology: toward a conceptual model of travel behaviour", *Transport Reviews*, 30 (2), 219–240.
- Xu et. al. (2017), "Optimal parking provision for ride-sourcing services", *Transportation Research Part B*.