Evaluating the travel impacts of a shared mobility system for remote workers

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Abstract

Given the rapid rise of remote work, there is an opportunity for new shared mobility services designed to meet the needs of passengers with multiple possible work locations. This paper develops a new optimization model to enable shared mobility systems to match drivers and passengers when passengers have flexible destinations. Constraints representing employer policies, such as mandatory co-location of colleagues and limited capacity of satellite offices are introduced in order to explore the impact of employer remote work policies on travel demand. A case study using historical demand data demonstrates that incorporating flexible work locations can increase ride-pooling participation by up to 6.7% and reduce vehicle-kilometers travelled by 4.9%. Outcomes are found to be significantly affected by employer policies. The implications of the results for shared mobility business models, employer remote work plans and local transportation policy are discussed.

Keywords: Shared Mobility, Remote Work, Travel Demand, Ride-pooling

1. Introduction

For the past century, individual commute patterns have typically involved a fixed destination that is stable over long periods of time. We are currently experiencing a profound shift in the nature of work, however. What was once a gradual trend towards increased remote work (Felstead and Henseke, 2017), driven by improvements in digital communication

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technology, the rise of the gig economy, and the emergence of co-working spaces was then suddenly and dramatically accelerated by the COVID-19 pandemic. A recent survey found that in 2023 and beyond, nearly a third of worked days in the United States are expected to be remote, a share that is more than six and a half times greater than the pre-pandemic average (Barrero et al., 2021). The same study finds that approximately one third of remote work in late 2021 and early 2022 was conducted outside the home. Beck and Hensher (2021) refer to this arrangement as "Working Close to Home". Figure 1 presents the distribution of full-time worked days in the United States by location; non-home remote locations include public spaces, co-working spaces and friends' homes.
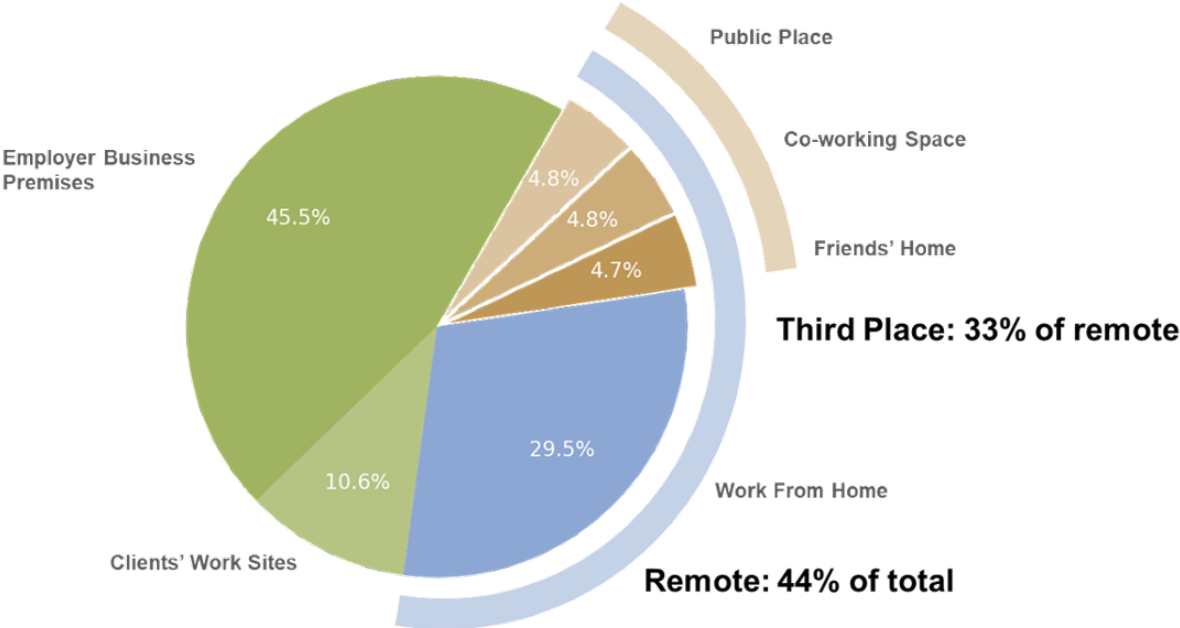

Figure 1: Distribution of work hours by location (Barrero et al., 2021). Survey waves from November 2021 to March 2022, N=21,136.

Even before COVID-19, some employers allowed staff to choose among several work locations on a day-to-day basis, including co-working spaces (Echeverri et al., 2021). This distributed office model is expected to become more popular in the future. A recent article (Bacevice et al., 2020) argues that employers should allow "hyper-local teams to choose a location based on their shared preference" in order to boost productivity and create "new

relationships within and among organizations." When multiple work locations are available, employees benefit from the opportunity to select a workplace that matches both their work and travel preferences. Innovative office solutions have quickly emerged to serve remote workers with flexible work locations; WeWork, a major co-working operator, has recently begun offering an all-access service where subscribers can choose to work from any location at any time (Thomas, 2021). There has been little innovation or research, however, regarding innovative mobility services that could serve remote workers with flexible work locations.

In this paper, a new analytical framework is introduced to enable simulation of a shared mobility system serving remote workers with multiple possible work locations. First, a novel matching algorithm is proposed that incorporates flexible destinations, location capacity constraints and team member co-location constraints. The impacts of these remote work constraints and objectives on ride-pooling adoption, quality of service and total travel demand are then explored for the first time in the literature through an experiment with real ride-hailing data from Manhattan. Finally, the implications of the results for future shared mobility providers, employer remote work policies and travel demand management are discussed.

Remote work locations represent an upending of the traditional travel demand modeling paradigm, wherein routine work trips are the anchor for daily travel patterns. In the past, urban mobility services such as public transit have been designed around serving stable commuting trips (McDonnell and Zellner, 2011). These designs may not fit the needs of commuters with remote work locations who will have many options for how, where, and when to travel. The benefits of remote work will only be realized if the mobility ecosystem can adapt to the new demands of remote work.

For example, one issue faced by remote workers with flexible work locations is coordinating the location of team members who are working on a collaborative task. Mobility services could respond by offering to arrange a location choice for multiple individuals that balances productivity considerations with travel costs. Other tasks, such as meeting a client

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or designing a product prototype might need specialized amenities that are only available at certain work locations. We propose a new terminology, "dependencies", to refer to these remote work constraints that must be incorporated into travel decisions. Employers would benefit from a mobility platform that can accommodate dependencies while arranging efficient travel for employees. Moreover, these dependencies will impact the destination choices of remote workers, affecting aggregate travel demand.

Providing mobility services that can meet these new demands is very challenging due to the number of possible dependencies: relationships between individuals, the characteristics of available destinations, task-related constraints that change over time, and so on. Exploring how these complex relationships affect the spatial distribution of travel demand will require the design of new analytical tools. Furthermore, the factors that affect workplace location choice include both travel and work preferences, two areas of study that are not often linked. Bridging the gap between travel behavior and organizational behavior is critical to preparing mobility systems for the future of work.

2. Literature Review

Remote work has long been of interest to transportation researchers, but there are few analytical models that connect remote work and transportation. The impacts of "teleworking" on urban travel were investigated as early as the 1970s; a report by Mokhtarian (1991) and review by Nilles (1988) provide a good summary of early empirical research. Recent changes in commuting patterns are expected to have a significant impact on the demand for travel along two important dimensions. First, a reduction in the overall volume of peak hour travel. Beck and Hensher (2021) predict a 20% reduction in urban core commuting post-pandemic. Second, a shift in the spatial distribution of demand away from commercial centers towards neighborhood centers, as remote workers have been shown to choose destinations that are closer to home than traditional commuters (Su et al., 2021). Additional empirical research includes studies of how remote work has affected road congestion in Iran

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(Vakilian and Edrisi, 2019) and Sweden (Bieser et al., 2021). A group of organizational behavior papers provide insight into the productivity considerations for remote work and co-working, but none include a transportation component (Martin and MacDonnell, 2012; Coenen and Kok, 2014; Ross and Ressia, 2015). There has also been research into the urban planning and real estate implications of flexible and remote work with limited discussion of transportation (Mariotti et al., 2021; Pajević, 2021).

One paper was found that included a simulation of a transportation system with remote work locations (Ge et al., 2018). The authors use an agent-based regional travel demand model to evaluate the effect of remote workplaces on commuting distances. Interestingly, they find that requiring co-location of teams can lead to a worse outcome than the status quo under certain conditions. The study does not include any mathematical modeling or productivity considerations, however.

Low occupancy ride-hailing trips represent a tremendous and problematic under-utilization of one of society's most expensive and in-demand resources: the road network. Most ride-hailing vehicles have a capacity of four passengers or more, yet the average occupancy is just 1.3 passengers (Henao and Marshall, 2019b). Ride-pooling is a ride-hailing service where multiple customers can be served by the same driver at the same time. This paper uses the ride-pooling mode to study the effects of remote work on transportation.

The primary areas of ride-pooling research are developing algorithms to improve operations and exploring supply and demand dynamics. A recent paper provides an excellent overview of the dynamics of ride-hailing platforms and their interactions with other urban mobility systems (Wang and Yang, 2019). Mourad et al. (2019) survey research into optimization techniques for shared mobility, which includes ride-hailing, while Agatz et al. (2012) review the literature in optimization for ride-hailing platforms specifically. Ke et al. (2021) explores the relationship between fleet size, maximum detour constraints, fare price, and other variables in a ride-pooling market. Other ride-pooling research studies the social dynamics of sharing rides (Zhang and Zhao, 2018; Moody et al., 2019).

In the past five years, a small number of papers have investigated the specific problem of ride-pooling with flexible destinations, suggesting a nascent but active subfield of research. Wang et al. (2016) develops a matching algorithm that considers multiple destinations for each passenger but treats alternative destinations as equivalent from the traveler perspective. Such a framework is not consistent with ride-pooling research such as Wang et al. (2019), which shows that perceived utility is the primary driver of decisions about pooled rides. Subsequent studies take a similar approach, where passenger utility is not considered during the destination assignment process. Mahin and Hashem (2019) develop a pruning technique to maximize ride-pooling, while de Lira et al. (2018) test a new heuristic algorithm, finding that flexible destinations and activity schedules increase pooled rides by up to 55%. Khan et al. (2017) develop a method of matching trips with flexible destinations using Steiner Trees to identify possible meeting points. Ride-pooling with flexible destinations based on a utility-maximization theory of travel behavior remains an unexplored research direction.

3. Remote work dependencies

First, a vocabulary is needed to categorize the relationships between people and places that affect work location choices. As proposed earlier, the term "dependency" will be used to refer to such relationships. Dependencies can exist between a person and workplace amenities ("location dependencies"), such as the requirement that a location includes a meeting room. Dependencies can also exist between a person and other people ("associate dependencies"). These associates might be coworkers needed for a face-to-face brainstorming activity, but also people with similar professions, people who work in the same industry, or even friends. Dependencies can be hard constraints or soft constraints (desirable but not necessary). They can be enforced by employers (top-down) or requested by individuals (bottom-up).

Second, it can be helpful to list common remote working arrangements, although any such list could never be considered exhaustive. Remote working arrangements can be considered a location-associates dyad. Working locations include spaces that are intended to be

workplaces (corporate office, home office, co-working space) and those that facilitate work as a secondary purpose (café, library, community center). Associates could include co-workers, friends, family, people with a similar profession, and so on. The relationship between the individual and these groups can be important for productivity or personal utility. Arrangements are constructed from a combination of one location and any number of associates. For example, a traditional working arrangement is the corporate office + co-worker pair. During the pandemic, many people became familiar with the home + no associates arrangement. Industry meetups, an arrangement where professional groups organize a collective remote work and networking event in a rented work space (i.e. co-working space + people with a similar industry) have been popular for some time (Bilandzic and Foth, 2016). There are many such combinations possible, each with different implications for mobility and productivity.

Finally, an analytical framework can now be established for transportation supply models that capture remote work dependencies. Each class of transportation mode has many models for optimizing service delivery, and each of these models interact differently with the remote work dependencies. This framework can be represented as a conceptual table with supply models on the vertical axis and remote work dependencies on the horizontal axis, as shown in Table 1. Each of the cells represents a possible supply-demand model that include the influence of remote work characteristics on a specific travel mode. The numbered cells are addressed in the case study that follows.

The capability of this structure to represent realistic scenarios is illustrated through a ride-pooling case study, which is just one element within the broader framework. The methods introduced in the case study are applicable to any mobility system where one or more passengers are matched with a vehicle in real time (e.g. demand-responsive transit, car-pooling, shared autonomous vehicles). First, a variable demand model is introduced to capture the choice between pooled and exclusive rides. Then a new ride-pooling supply model that permits multiple destination options and facilitates the inclusion of remote work dependencies is developed. Finally, new constraints and objective function terms are

Travel mode		Remote work characteristics			
		Flexible destinations	Location dependency	Associate dependency	Other
Public	Fixed route transit				
	Flexible transit				
Shared	TNCs and taxis				
	Ride-pooling	I	II	III	
	Shared AVs				
	Micromobility				
Private	Active travel				
	Private gas car				
	Private electric car				
	Private AV				

Table 1: Conceptual table for the mobility and remote work analytical framework

proposed to capture the location and associate dependencies.

4. Adding dependencies to shared mobility models

Now that a vocabulary for describing remote work dependencies and arrangements has been established, we will demonstrate how to incorporate them into a ride-pooling matching model in order to evaluate their impact on the transportation system. Dependencies affect demand, and because the supply is responsive to demand, they ultimately affect supply as well. This requires three substantial modifications to existing ride-pooling models, which are represented by Roman numerals in Table 1. The first set of modifications (Cell I) is simply to create a ride-pooling matching model that allows the passenger to choose between multiple alternative destinations. As discussed in the Literature Review section, previous models consider destinations to be fixed, or to be controlled by the platform.

The second modification (Cell II) is to add a location dependency to the supply model. In this case we consider a scenario where remote workers would like to visit one of several co-working spaces, but there is a limited number of available workplaces at each location. The ride-pooling platform must incorporate these capacity constraints when finding an optimal ride-pooling matching arrangement for the remote workers. This location dependency is

used to explore the travel implications of co-working space capacity and geographic location within an urban area.

The third modification (Cell III) is to add two different associate dependencies: hard constraints and preferences. The hard constraint represents a requirement that different combinations of people (members of the same project team, for example) must work in the same location, but the choice of location is flexible. The preference dependency can be modelled by assuming that the ride-pooling platform receives a small premium for arranging rides such that certain combinations of employees work in the same location. This assumes that the employees perceive a benefit from being co-located with their team members and are willing to compensate the ride-pooling platform some small amount in exchange for that benefit. One could also imagine an employer bearing this additional cost through reimbursement in an effort to encourage face-to-face interactions between remote employees. The practice of reimbursing travel costs for remote workers to get together in-person has recently been adopted by several large employers (Abril, 2022). This dependency provides a connection between organizational behavior and transportation outcomes in order to demonstrate how remote work policies can impact travel patterns.

4.1. Adding flexible destinations (I)

There are two distinct components involved in adding flexible destinations to a shared mobility matching algorithm. Existing algorithms must be adapted to allow vehicle-customer matching across several possible destinations. In addition, there must be a choice model to capture the customer's choice of a single destination from a set of possible destinations once the trip characteristics are known.

4.1.1. Destination choice model

In the ride-pooling case study, total travel demand is fixed but individual customers ("agents") can choose between a pooled ride and an exclusive ride. Consider a set of agents $\mathcal{A}$ indexed by j and a set of all pooled and exclusive trips $\mathcal{T}$ indexed by i. Note that in

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this paper, the term "trip" is used to denote a supply-side variable: a *vehicle* trip that is either a pooled ride (multiple passengers) or exclusive ride. It should not be confused with a passenger journey between an origin and destination, which is also described as a "trip" in other contexts. All notation used in this paper can be found in Tables 2 - 4.

Some agents have a fixed destination, while others indicate willingness to consider multiple alternative destinations. These alternative destinations could represent several decentralized offices operated by agent's employer, or a set of co-working spaces, or even nearby libraries or cafés. These alternative destinations could be served by either a pooled or exclusive ride. To model the choice between different ride types (pooled vs. exclusive) and different destinations, we use a mixed logit discrete choice model, which has been found to provide a reasonably good fit for the mode choice between exclusive and pooled rides (Alonso-González et al., 2020). Our model differs from existing ride-pooling choice models by incorporating a destination utility term to represent the traveler's varied preferences for alternative destinations. It also introduces a deterministic pricing model for the pooled ride discount.

Notation	Definition
$\mathcal{A}$	Set of all agents
j	Agent index
$\mathcal{D}$	Set of all destinations
d	Destination index
$\mathcal{T}$	Set of all trips
i	Trip index
$\mathcal{V}$	Set of all available vehicles
k	Vehicle index
$\mathcal{E}_{AT}$	Set of agent-trip pairs in the shareability graph
$\mathcal{E}_i^V$	Set of vehicles that can serve trip i

Table 2: Notation for sets and set indices

The utility function for the discrete choice model is shown in Eq. 1. Total utility of an exclusive ride trip i for agent j, V_{ij}, is a linear function of the destination utility (v_{ij}), the exclusive ride fare price (c_{ij}) and the shortest path travel time (t_{ij}). Exclusive ride fare price is assumed to be a linear function of travel time and distance. If trip i is a pooled ride

Notation	Definition
V_{ij}	Deterministic utility of trip i for agent j (utility)
v_{ij}	Destination utility derived from trip i for agent j (utility)
c_{ij}	Exclusive ride fare price for trip i charged to agent j (\$)
c_{ij}^s	Pooled ride discount of trip i for agent j (\$)
t_{ij}	Shortest path travel time for agent j on trip i (min)
δ_{ij}	Pooled ride detour of trip i for agent j (min)
ζ_i	Binary pooled ride indicator for trip i where $\zeta_i = 1$ if trip i is a pooled ride
β_1	Cost coefficient (utility / \$)
β_2	Time coefficient (utility / min)
β_3	Sharing penalty (utility)
U_{ij}	Total utility of trip i for agent j (utility)
ε	Random deviate representing unobserved determinants of utility (utility)

Table 3: Notation for demand model

trip, there is also a pooled ride discount c_{ij}^s, a pooled ride detour time (δ_{ij}) and a binary pooled ride indicator (ζ_i) that models the inconvenience of sharing a vehicle with a stranger. Kang et al. (2021) find that the inconvenience of sharing is fixed with respect to travel time. Coefficients $\beta_1, \beta_2, \beta_3$ convert the cost, travel time and sharing penalty terms into units of utility.

$$V_{ij}(v_{ij}, c_{ij}, c_{ij}^s, t_{ij}, \delta_{ij}, \zeta_i) = v_{ij} - \left[\beta_1(c_{ij} - c_{ij}^s) + \beta_2(t_{ij} + \delta_{ij}) + \beta_3\zeta_i \right] \tag{1}$$

The pricing algorithms used by ride-pooling platforms in practice are not available to the public, so a deterministic pooled-ride pricing algorithm is assumed. Pooled rides reduce operating costs by serving several passengers simultaneously, and a portion of these savings is passed on to customers as a fare discount. For a pooled ride to present an attractive alternative to an exclusive ride, $\beta_1 c_{ij}^s$ must be greater than $\beta_2\delta_{ij} + \beta_3\zeta_i$ for each passenger.

The profit for each trip is determined by taking the sum of the fare paid by all passengers and subtracting the operating costs, which are linear functions of the travel time and travel distance. To maximize profit, the operator offers the minimum discount such that each passenger experiences an increase in utility over an exclusive ride and retain the remainder of the pooled ride savings as profit. The operator cannot know each agent's sensitivity to

Notation	Definition
x_i	Binary trip served indicator where $x_i = 1$ if trip i is included in the optimal matching arrangement
y_{ij}	Binary agent-trip assignment indicator where $y_{ij} = 1$ if agent j is assigned to trip i
z_j	Binary unserved agent indicator where $z_j = 1$ if agent j is unserved
w_{ik}	Binary vehicle-trip assignment indicator where $w_{ik} = 1$ if trip i is served by vehicle k
q_{jd}	Binary agent-destination indicator where $q_{jd} = 1$ if agent j is assigned to destination d
p_i	Nominal operator profit associated with trip i (\$)
$\bar{p}_i$	Expected operator profit associated with trip i (\$)
λ_{ik}	Cost of assigning vehicle k to serve trip i (\$)
M	Operator penalty for one unserved agent (\$)
Q_{ijd}	Binary correspondence matrix defining correspondence between an agent-trip pair (i, j) and an agent-destination pair (j, d), where $Q_{ijd} = 1$ if trip i results in agent j traveling to destination d
b_d	Maximum occupant capacity of location d (occupants)
μ_{jmd}	Binary agent co-location indicator, where if agents $\mu_{jmd} = 1$ if agent j and agent m are assigned to destination d
$u_{jd}^{\max}$	Maximum possible profit incurred from assigning agent j to destination d (\$)
I_{jmd}	Fraction of maximum benefit produced when agents $j, m \neq j$ are assigned to destination d (%)
u_{jd}	Total fraction of maximum benefit gained from assigning agent j to destination d (%)
α_{jd}	Substitution variable representing the realized fraction of additional profit from assigning passenger j to destination d (%)
g_{jd}	Binary auxiliary variable used to enforce the conditional relationship between $\alpha_{jd}, u_{jd}, q_{jd}$

Table 4: Notation for supply model

price, detour and sharing, so instead assume that the operator chooses some constant fraction of the operating cost savings to return as a discount to passengers. The total discount is then distributed among the passengers according to their relative excess disutility. As a result, if the total passenger discount is greater than the total excess disutility, it is guaranteed that all passengers will have a lower travel cost for the pooled ride.

The discrete choice model is incorporated by adding a new step in the matching process. The platform provides pooled ride trip characteristics (fare discount, detour time) to each agent. Then, the discrete choice model simulates the choice by each agent between a pooled

ride or an exclusive ride. The utility calculated in Eq. (1) is used as an input to determine each agent's choice between alternative pooled rides and exclusive rides. It is common practice in travel demand modeling to include a random utility deviate, ε, to capture the unobserved determinants of utility between alternatives. There are many different distributions used for ε; extreme value distributions are popular for their fit and tractability (Train, 2009). The total demand for exclusive and pooled ride trips, determined from the random utility discrete choice model, is then used to construct the shareability graph for the optimal matching model described in the next section.

4.1.2. Matching with flexible destinations

The parameters for each pooled ride can be determined by finding the optimal matching arrangement for a set of ride-pooling requests. The intuition for the matching algorithm is adopted from Alonso-Mora et al. (2017), wherein a graph structure is created to identify possible vehicle-agent combinations, and then an optimization model is solved to select the optimal set of pooled rides. The procedure is generally tractable, even for the large vehicle capacities that would be needed for demand-responsive transit or van-pooling, making it an attractive approach for this application. An entirely new shareability graph structure and generation procedure is developed in order to enable efficient matching despite the added complexity of flexible destinations. Furthermore, a novel integer programming formulation with destination-specific decision variables is proposed for the optimal matching problem that permits remote work dependencies such as team co-location requirements. Together, these create a new passenger-vehicle-destination matching algorithm to evaluate the implications of remote work policies for shared mobility.

First, the set of shareable rides must be identified. Assume that during some fixed time interval, a certain number of agents make requests for travel. Requests are shareable so long as constraints on waiting time, detour time and vehicle passenger capacity are met. Another restriction is also added: the operating cost of a pooled ride cannot exceed the total operating cost of serving each agent with an exclusive ride. This ensures that only pooled

rides which produce additional profit for the operator are considered. Any pooled rides that violate this restriction are not included in the shareability graph and therefore cannot be chosen by passengers. Additionally, agents whose trips are not shareable with another agent are served by an exclusive trip.

In the original algorithm each request corresponds to a separate agent. Destination flexibility is modeled by including multiple requests from the same agent with different destinations. Two requests associated with the same agent are not shareable with each other. The new shareability graph involves 4 different node types: agents, requests, trips, and vehicles. The graph representation permits a new constraint to ensure that only one request per agent is assigned in the optimal solution.

A simple example is shown in Figure 2. The circular nodes represent requests (origin-destination pairs) associated with each agent. Each request node has an in-degree of 1, meaning that only one agent is associated with each request. In this case, Agent #2 has flexible destinations, represented by the 3 yellow request nodes connected to Agent #2. Requests by different agents are combined into possible pooled ride "trips" served by a single vehicle. Note that the three requests from Agent #2 have no trips in common, as it would not be feasible for Agent #2 to be involved in multiple pooled rides at the same time. Finally, each of the potential trips can be served by one or more vehicles.

Once the shareability graph is constructed, an integer linear program (ILP) is solved to find the optimal assignment of agents and vehicles to trips. This assignment occurs twice: an initial assignment to provide pooled ride trip parameters to the agents before the actual demand is realized, and a final assignment for the agents who select pooled rides. For the final assignment, nodes corresponding to requests that choose an exclusive ride are pruned from the shareability graph, and the optimal matching arrangement is redetermined. The overall matching and passenger choice process is illustrated in Fig. 3. The final assignment occurs over a subgraph of the initial shareability graph and does not add significant computation time.
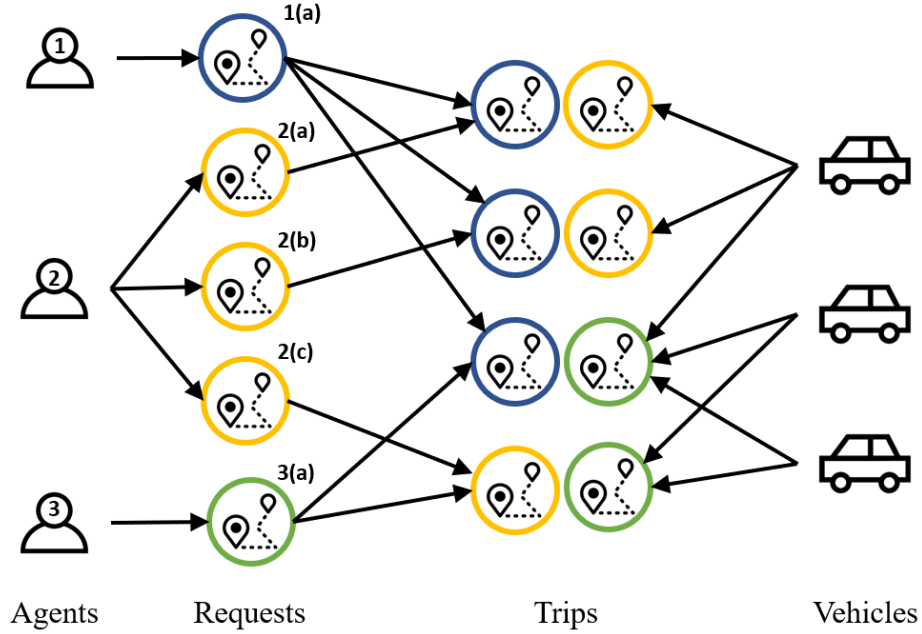
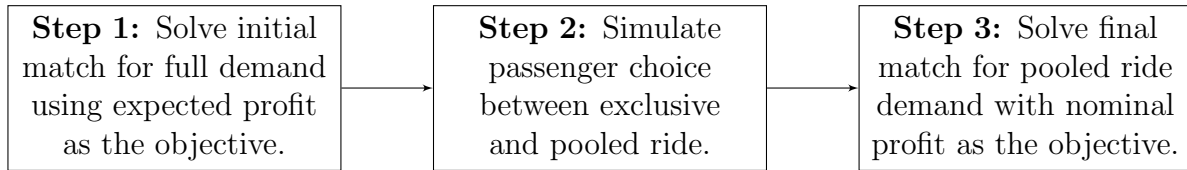Figure 2: Example of the agent-request-trip-vehicle shareability graph

Step 1: Solve initial match for full demand using expected profit as the objective.	**Step 2:** Simulate passenger choice between exclusive and pooled ride.	**Step 3:** Solve final match for pooled ride demand with nominal profit as the objective.

Figure 3: Flow chart demonstrating the matching and passenger choice process

The initial matching assignment is based on unrealized demand; ultimately some of the pooled rides will not be feasible because the agents involved will choose an exclusive ride. Therefore, the matching should be weighted towards pooled trips that are most likely to be chosen by all agents involved. This can be accomplished by using *expected* profit in the objective function rather than the nominal profit. The probability that a pooled ride is chosen by all agents can be estimated in advance for each trip through simulation of the discrete model described in the previous section. In the final assignment, the demand is fixed and the nominal profit is used in the objective function. The two models are otherwise identical.

This process was designed to be similar to the actual ride-hailing customer experience. The user indicates their travel plans, the platform responds with a set of prices and travel

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times, then the user chooses from one of the alternatives. Note that the process is naïve in that it does not assume any learning of consumer preferences over time. In reality, the platform may take advantage of their users' responses to design better recommendation algorithms or pricing strategies.

4.2. Location dependency (II)

The model developed in the previous section enables general ride-pooling matching with destination flexibility. To capture remote work dependencies, additional constraints and different objective functions can be formulated. For example, consider a ride-pooling platform and co-working service that each have a large market share. All co-working locations are available to the agents, but there are a limited number of seats at each location. The ride-pooling platform should be aware of facility capacities and therefore avoid routing a large number of passengers to any single location regardless of centrality or travel convenience. The ride-pooling matching ILP described in Alonso-Mora et al. (2017) does not contain any variables related to destination, so a new model is created to allow for location dependencies. Additional indices are defined for the new ILP: $k \in \mathcal{V}$ for vehicles, and $d \in \mathcal{D}$ for destinations. The set of vehicles that can be assigned to trip i is $\mathcal{E}_i^V$. Each trip produces a nominal profit p_i for the operator, while the expected profit is denoted by $\bar{p}_i$. The cost of assigning vehicle k to trip i due to vehicle relocation is represented by λ_{ik}.

The binary decision variables are chosen to permit constraints and objective terms dependent on destination choice, which are important for modeling the dynamics of remote work trips. Let $x_i \in \{0,1\}$ indicate whether trip i is served, and $y_{ij} \in \{0,1\}$ indicate whether agent j is assigned to trip i. Let $z_j \in \{0,1\}$ indicate whether agent j is unserved and $w_{ik} \in \{0,1\}$ indicate whether trip i is served by vehicle k. Finally, let $q_{jd} \in \{0,1\}$ indicate whether agent j is assigned to a trip with destination d. This destination-related decision variable is an important addition to enable associate and location dependencies. Since each agent-trip pair (i,j) corresponds to exactly one destination, a correspondence matrix $\mathbf{Q}$ can be created where $Q_{ijd} = 1$ if trip i results in agent j visiting destination d, and $Q_{ijd} = 0$

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otherwise. The initial ILP can then be formulated as follows:

$$\max_{q,w,x,y,z} \quad Z_0 = \sum_{i\in\mathcal{T}}\left(\bar{p}_i x_i - \sum_{k\in\mathcal{E}_i^V}\lambda_{ik}w_{ik}\right) - M\sum_{j\in\mathcal{A}}z_j \tag{2a}$$

$$\text{s.t.} \quad x_i \leq y_{ij} \qquad\qquad\qquad \forall(i,j)\in\mathcal{E}_{AT} \tag{2b}$$

$$Q_{ijd}y_{ij} = q_{jd} \qquad\qquad \forall(i,j)\in\mathcal{E}_{AT}; d\in\mathcal{D} \tag{2c}$$

$$x_i \leq \sum_{k\in\mathcal{E}_i^V} w_{ik} \qquad\qquad\qquad \forall i\in\mathcal{T} \tag{2d}$$

$$\sum_{i\in\mathcal{T}} w_{ik} \leq 1 \qquad\qquad\qquad \forall k\in\mathcal{V} \tag{2e}$$

$$\sum_{i\in\mathcal{T}} y_{ij} - z_j = 0 \qquad\qquad\qquad \forall j\in\mathcal{A} \tag{2f}$$

$$\mathbf{q},\mathbf{w},\mathbf{x},\mathbf{y},\mathbf{z}\in\{0,1\} \tag{2g}$$

Function 2a maximizes total expected trip profit less the cost of vehicle assignments. A large penalty M is applied for all unserved agents. For the final matching model, the $\bar{p}_i$ term in 2a is replaced with p_i. Constraint 2b requires that the agents involved in a pooled trip are assigned to the trip if the trip is served. Constraint 2c defines the relationship between y_{ij} and q_{jd} such that $q_{jd} = 1$ if agent j is assigned to a trip where the agent's destination is d ($y_{ij} = 1$ and $Q_{ijd} = 1$), and $q_{jd} = 0$ otherwise. Constraint 2d ensures that each served trip has an assigned vehicle. Constraint 2e requires each vehicle to serve one trip at most. Constraint 2f ensures that each agent is either assigned to one trip or unserved.

Finally, the location capacity limit is modeled by adding the following constraint on q_{jd}, where b_d is the number of available seats at location d:

$$\sum_{j\in\mathcal{A}} q_{jd} \leq b_d \qquad\qquad\qquad \forall d\in\mathcal{D} \tag{3}$$

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4.3. Associate dependencies (III)

First, a hard associate dependency is added to the ILP to ensure certain individuals are assigned to the same location, perhaps team members who require face-to-face interaction to accomplish a task. The dependency is enforced by adding a constraint of the following form for two agents $j, m \neq j$:

$$\sum_{d \in \mathcal{D}} q_{jd} q_{md} = 1 \tag{4}$$

This is a non-linear constraint in the decision variables however, which makes the model much harder to solve. The non-linearity can be overcome by introducing $|\mathcal{D}||\mathcal{A}|^2$ new binary decision variables, $\mu_{jmd} \in \{0, 1\}$ to represent the non-linear term $q_{jd} q_{md}$. Four linear constraints can be used to model the conditional relationship between μ_{jmd} and $q_{jd} q_{md}$, where $\mu_{jmd} = 1$ if $q_{jd} q_{md} = 1$ and 0 otherwise:

$$\mu_{jmd} \leq q_{jd} \qquad\qquad \forall j, m \neq j \in \mathcal{A}, d \in \mathcal{D} \tag{5a}$$

$$\mu_{jmd} \leq q_{md} \qquad\qquad \forall j, m \neq j \in \mathcal{A}, d \in \mathcal{D} \tag{5b}$$

$$\mu_{jmd} \geq q_{jd} + q_{md} - 1 \qquad\qquad \forall j, m \neq j \in \mathcal{A}, d \in \mathcal{D} \tag{5c}$$

$$\mu \in \{0, 1\} \tag{5d}$$

Similar dependencies can be enforced using this linear formulation, such as a requirement that each employee work at the same location as at least one team member. The initial non-linear constraint in Eq. 4 is replaced by the following equation, and the same linearization techniques described above are applied:

$$\sum_{m \in \{\mathcal{A} \setminus j\}} \sum_{d \in \mathcal{D}} q_{jd} q_{md} \geq 1 \qquad\qquad \forall j \in \mathcal{A} \qquad\qquad (6)$$

The second associate dependency, which is a soft constraint, is introduced by changing the objective function. The model structure also allows for more complex objective functions that include remote work considerations. For example, imagine a version of the scenario described above where two people benefit from face-to-face interaction, but the interaction is simply preferred instead of required. Since the destination of each passenger is a decision variable in the ride-pooling matching model, it is not known in advance. Recall that in this scenario, the employer compensates the ride-pooling platform for co-location of employees to encourage higher productivity. This provides an incentive for the ride-pooling platform to choose an otherwise suboptimal matching arrangement as long as it results in the co-location of certain employees. For simplicity, assume that each co-located pair of team members results in a constant payment, regardless of location. This framework can, however, include payments that vary by employee and location.

There is then some maximum amount of payment that can be obtained by locating agent j at location d, which occurs when all the team members of agent j are also located at d. This maximum payment is represented by a constant, $u_{jd}^{\max}$. A matrix I of size $|\mathcal{A}| \times |\mathcal{A}| \times |\mathcal{D}|$ is defined, where $I_{jmd} \in [0, 1]$ is the fraction of $u_{jd}^{\max}$ obtained when agent m is co-located with agent j at destination d. In this simple case, I_{jmd} is equal to 1 over the size of the team, therefore $\sum_m I_{jmd} = 1$.

There are two conditions required for the payment to be realized. First, the team members must be co-located with agent j. The auxiliary variable $u_{jd} \in [0, 1]$, is introduced to represent the fraction of $u_{jd}^{\max}$ that could be accrued when agent j visits location d, given that some of the team members may not be co-located at d (i.e. $u_{jd} = \sum_{m \in \{\mathcal{A} \setminus j\}} I_{jmd} q_{md}$). Second, agent j must be assigned to destination d, which occurs when $q_{jd} = 1$. Multiplying

decision variables u_{jd} and q_{jd} produces a non-linear term in the objective function, however. This binary-continuous product can be linearized through substitution. First, let $\alpha_{jd} \in [0,1]$ represent $u_{jd}q_{jd}$. An auxiliary variable g_{jd} and constraints (8a) - (8f) are introduced to enforce $\alpha_{jd} = u_{jd}$ when $q_{jd} = 1$ and $\alpha_{jd} = 0$ otherwise. The objective function in Eq.(2a) is replaced by a new objective function:

$$\max_{q,w,x,y,z,u,\alpha,g} Z_1 = \sum_{i \in \mathcal{T}} (\bar{p}_i x_i - \sum_{k \in \mathcal{E}_i^V} \lambda_{ik} w_{ik}) - M \sum_{j \in \mathcal{A}} z_j + \sum_{j \in \mathcal{A}} \sum_{d \in \mathcal{D}} u_{jd}^{\max} \alpha_{jd} \tag{7}$$

The linear constraints are as follows:

$$u_{jd} = \sum_{m \in \{\mathcal{A}\setminus j\}} I_{jmd} q_{md} \qquad\qquad \forall j \in \mathcal{A}, d \in \mathcal{D} \tag{8a}$$

$$-g_{jd} \leq q_{jd} \leq g_{jd} \qquad\qquad \forall j \in \mathcal{A}, d \in \mathcal{D} \tag{8b}$$

$$1 - (1 - g_{jd}) \leq q_{jd} \leq 1 + (1 - g_{jd}) \qquad\qquad \forall j \in \mathcal{A}, d \in \mathcal{D} \tag{8c}$$

$$-g_{jd} \leq \alpha_{jd} \leq g_{jd} \qquad\qquad \forall j \in \mathcal{A}, d \in \mathcal{D} \tag{8d}$$

$$-(1 - g_{jd}) \leq (\alpha_{jd} - u_{jd}) \leq (1 - g_{jd}) \qquad\qquad \forall j \in \mathcal{A}, d \in \mathcal{D} \tag{8e}$$

$$\mathbf{g} \in \{0,1\} \quad \alpha \in [0,1], \quad \mathbf{u} \in [0,1] \tag{8f}$$

A total of $3|\mathcal{D}||\mathcal{A}|$ new decision variables, some continuous, are introduced to create a tractable mixed-integer program with a linear objective and linear constraints. This enables the ride-pooling matching problem to be solved efficiently for the co-working scenario. The objective is defined in Eq. (7), subject to constraints (2b) - (2f), (3) and (8a) - (8f).

5. Case Study

5.1. Experiment design

To demonstrate how the methods described in the previous section can be used to design ride-pooling services for remote work, an experiment was developed using real ride-hailing

demand data from Manhattan. Exact origins, destinations, and pickup times for each trip in June 2016 were collected from a public dataset provided by the New York City Taxi and Limousine Commission (NYCTLC, 2016). Time-dependent travel speeds for each street in Manhattan were used to determine travel times between pickup and drop-off locations (Uber, 2019). Ride-pooling requests were grouped into 3-minute intervals during the morning rush hour (8 AM - 9 AM), a time period during which the vast majority of travelers are traveling to work. The interval starting at 8:00 AM was used for this experiment, which contained 840 requests. The vehicle fleet size was therefore chosen to be sufficient to satisfy the demand; initial vehicle locations were assigned uniformly at random from the set of street intersections. The values for all simulation parameters are presented in Table 5.

Parameter	Value
Cost coefficient mean (β_1)	1.59 (Alonso-González et al., 2020)
Time coefficient (β_2)	0.318 (Alonso-González et al., 2020)
Sharing coefficient (β_3)	0.693 (Alonso-González et al., 2020)
Maximum wait time	10 minutes
Maximum detour time	25% of shortest path travel time
Fleet size	900 vehicles
Vehicle capacity	4 passengers
Base fare	$2.65 (Henao and Marshall, 2019a)
Additional fare per mile	$1.005 / mile (Henao and Marshall, 2019a)
Additional fare per minute	$0.1125 / minute (Henao and Marshall, 2019a)
Exclusive ride profit margin	25% (Henao and Marshall, 2019a)
Pooled ride profit margin	50% of operating cost savings
Total number of agents	840 agents
Agents with flexible destinations	168 agents (20% of total)
Available co-working locations	10 Manhattan WeWork locations
Optimality gap cut-off	0.5%

Table 5: Simulation Parameters

Values for β_1, β_2 and β_3 were adopted from the ride-pooling discrete choice model estimated by Alonso-González et al. (2020). The maximum pickup time was set to 10 minutes and the maximum detour was set to 25% of the shortest path travel time. Operating parameters for ride-pooling platforms are taken from a 2019 study of Uber and Lyft in Denver, CO (Henao and Marshall, 2019a). Ten evenly spaced WeWork spaces in Manhattan are used as

the representative remote work locations (WeWork, 2021). The destination utilities v_{ij} are unknown in practice, so a distribution is assumed. For each agent, the utility is sampled independently from a mixed distribution for each location such that the agents have similar but not identical utility for each destination. The mixed distribution is a normal distribution where the mean is drawn uniformly at random from the range $(50, 60)$ for each destination, with a standard deviation of 3 units.

Three scenarios are tested against a baseline scenario. The first demonstrates how remote work locations affects ride-pooling outcomes compared to a baseline where all locations are fixed. In the typical remote work scenario, 20% of passengers are assumed to have flexible destinations. Values from 5% to 30% are tested for Scenario 1. Passengers with flexible destinations are chosen at random as no employment or demographic information is provided about the passengers in the NYCTLC dataset. These passengers choose between trips to each of the 10 selected WeWork locations. Because the destinations were changed to WeWork locations for Scenario 1, the locations are also changed in the baseline scenario to ensure that only the effect of passengers with multiple flexible destinations influence the results. To that end, all passengers with a flexible destination in Scenario 1 are assigned to the WeWork location with the least travel cost in the baseline scenario. The sensitivity of the results to the quantity and layout of these locations are also tested in Scenario 1 by re-running the experiment with 5 and 15 WeWork locations.

Scenario 2 adds different location capacity constraints from Eq. (3) to explore the impact of co-working space size on ride-pooling outcomes. Finally, the third scenario incorporates the associate constraints and dependencies described in contrasts the results of the associate dependency benefits from Eqs. (6) - (8) with the results from the two previous scenarios. Each scenario is evaluated on the basis of operator profit, pooled ride mode share, total vehicle-miles traveled (VMT), total agent utility and solution time. The reported results are the average of 10 model runs as the demand model includes a stochastic discrete choice component, although the results do not vary significantly across simulation runs (the coefficients

of variation are less than 3%).

5.2. Results

Table 6 compares the ride-pooling outcomes for different levels of passenger flexibility against equivalent baseline scenarios with no flexible destinations. Percentage changes in performance relative to the corresponding baseline scenario are reported. The results demonstrate that flexible destinations allows the ride-pooling platform to match travelers more efficiently, leading to a greater share of pooled rides, lower VMT and more operator profit. Moreover, performance increases with respect to VMT, profit and number of pooled trips grow rapidly with the share of flexible passengers. The average utility for passengers is unchanged across scenarios, indicating that the discount for the additional pooled trips is sufficient to offset the disutility of sharing. The maximum ILP solution time for all experiments was 11.3 seconds using Gurobi v9.1 on a dual-core Intel i7-6600U CPU with 16GB of RAM.

The reduction in VMT observed in the flexible destination scenario is entirely due to matching efficiency. Flexible destinations led to slightly longer trips being selected on average: the total *passenger* miles travelled (PMT) increases in the flexible scenario relative to the baseline scenario, indicating that the reduction in VMT is purely a consequence of the greater number of pooled trips. In brief, flexible destinations result in each vehicle mile serving more passenger miles.

Evaluation Parameter	Share of passengers with flexible destinations				
	5%	10%	15%	20%	25%
Number of Pooled Trips	+1.3%	+1.8%	+2.7%	+4.1%	+6.3%
Operator Profit	+0.6%	+1.6%	+3.2%	+5.3%	+8.4%
Passenger Utility	+0.1%	+0.1%	+0.0%	+0.0%	+0.2%
Total VMT	-0.4%	-0.8%	-1.8%	-3.2%	-4.9%
PMT / VMT	+0.8%	+0.8%	+1.9%	+5.3%	+5.4%

Table 6: Ride-pooling platform performance with flexible destinations relative to non-flexible scenario by share of flexible passengers

These results are encouraging; even with a low share of flexible travelers, outcomes are

improved for all stakeholders. It is unsurprising that the benefit of passengers having flexible destinations yields the greatest benefits for the operator (profit) and the system (VMT and pooled trips), rather than the passengers themselves, given that objective of the ILP is to maximize operator profit. The increases to passenger utility appear to be largely incidental and are not affected by the share of passengers with flexible destinations. The efficient matching afforded by destination flexibility has positive externalities, namely reduced travel due to a higher pooling rate. It is perfectly reasonable to assume that the objective of the platform is to maximize profit, but other objective functions, perhaps achieved through regulation or through a different incentive structure, could distribute the benefits differently.

The sensitivity of the results with respect to the number and spatial distribution of possible destinations provides insights into the impact of land use and available flexible workplaces on travel demand. The baseline scenario used to generate the results presented in Table 6 assumes there are 10 flexible workplaces available, with the locations corresponding to actual WeWork spaces in Manhattan. The simulation was also run for scenarios with 5 and 20 destinations, also selected from WeWork offices. The spatial distribution of the locations is presented in Figure 4a below. The number of visits by location for the 20 destination scenario are presented in Figure 4b.

Table 7 shows how the performance of the ride-pooling platform changes with respect to the number of destinations available to flexible travelers. Once again, the percentage improvement relative to the non-flexible baseline for each scenario is reported. Clearly a greater number of flexible destinations available to flexible passengers creates more opportunity for efficient matching by expanding the shareability graph, leading to better performance and reduced externalities. Interestingly, PMT declines when 20 destinations are available relative to the 10 destination scenario because passengers are more likely to find an available destination nearby. As a result, the reduction in VMT is not a result of increased efficiency, but simply a result of shorter overall trip distances.

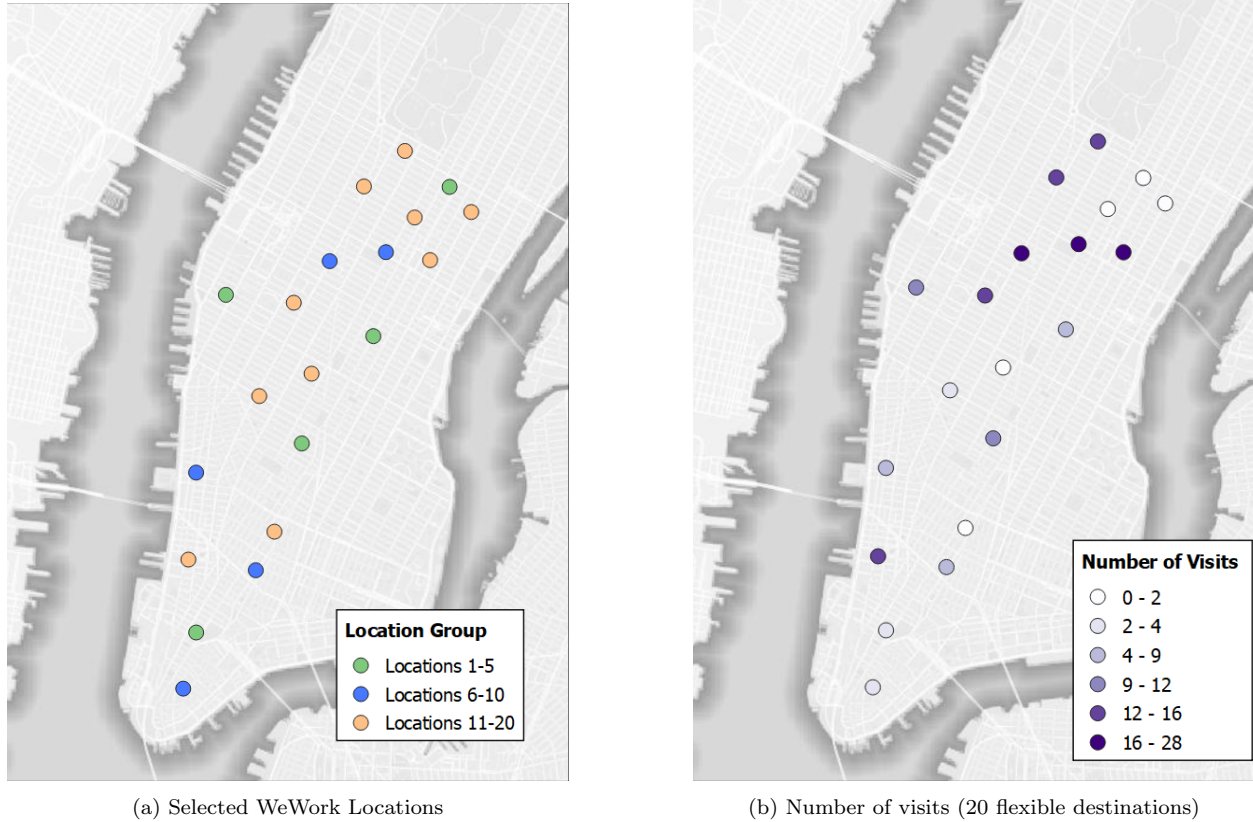Scenario 2 adds location capacity constraints to the problem to model the ride-pooling

(a) Selected WeWork Locations

(b) Number of visits (20 flexible destinations)

Figure 4: Spatial distribution of flexible work locations and visits

Evaluation Parameter	Number of available destinations		
	5	10	20
Number of Pooled Trips	+0.5%	+4.1%	+6.7%
Operator Profit	+3.1%	+5.3%	+6.2%
Passenger Utility	+0.0%	+0.0%	+0.0%
Total VMT	-2.3%	-3.2%	-4.0%
PMT / VMT	+0.5%	+2.0%	+1.2%

Table 7: Ride-pooling platform performance with flexible destinations relative to non-flexible scenario by number of available destinations for flexible passengers

problem for a co-working location or an employer with several small offices in an urban area. In the unconstrained problem, the most popular destination was visited by 50 agents. Figure 5 presents the trends for traveler utility and VMT as several increasingly restrictive occupant capacities are applied. The effects are limited for maximum capacity constraints above 35 people per location as only a few trips to the most popular locations are affected. As the maximum capacities grow smaller, however, traveler welfare (as measured by utility)

and system outcomes (VMT) begin to decline quickly. The most restrictive location capacity constraints decrease total traveler utility by 9.0% while increasing VMT by 6.6%, as the constraints force many remote workers to travel to less preferred and more distant locations. These impacts fall entirely on the remote workers, as they are the only travelers who can change their destinations in response to capacity constraints. The average travel distance for remote workers is 1.96 miles in the unconstrained scenario and 2.30 miles in the most constrained scenario.

The implications of these results are that, in a remote work environment, workplaces that are easily accessible by remote workers will experience greater demand on a day-to-day basis. If demand begins to exceed the number of available workplaces at these centrally located remote work hubs, overall congestion will increase as remote workers must travel further to find an available space. Policy makers interested in travel demand management may consider tracking occupancy rates of remote work spaces in their regions and removing regulatory barriers to expansion where demand exceeds supply.
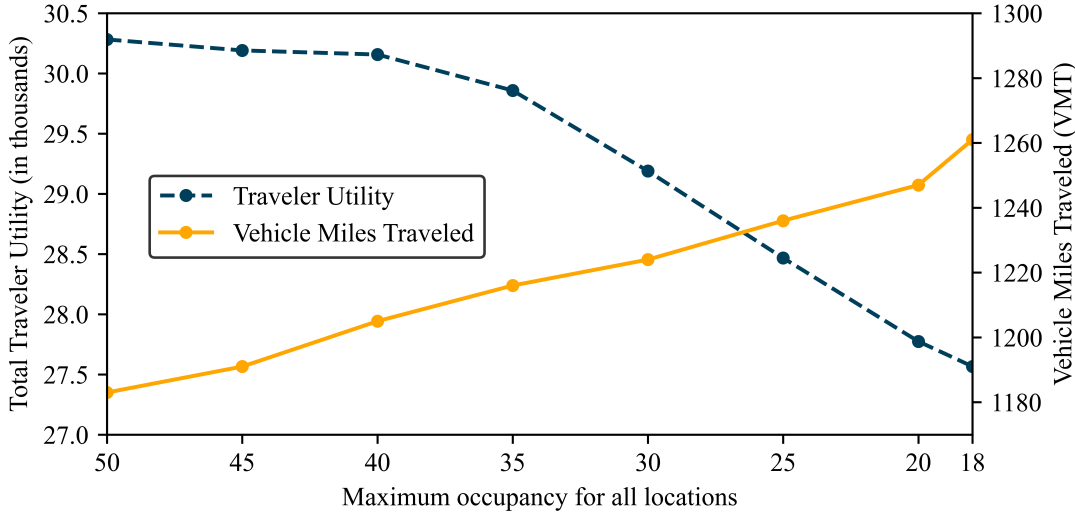

Figure 5: Sensitivity of total traveler utility and VMT to changes in location capacity

Finally, Scenario 3 adds associate dependencies to the objective function as given by Eqs. (6) - (8) while removing the location capacity constraint. The first is a hard constraint requiring each flexible traveler to be co-located with a certain number of their colleagues.

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Figure 6 shows how co-locating two employees hardly effects the travel outcomes, but co-locating three or more colleagues results in a major degradation in performance. The co-location constraint forces flexible workers to destinations that are significantly suboptimal from a transportation efficiency perspective, limiting the amount of matching that occurs and driving up VMT. Traveler utility decreases as longer and more expensive trips are required to less desirable destinations in order to satisfy the co-location constraint.
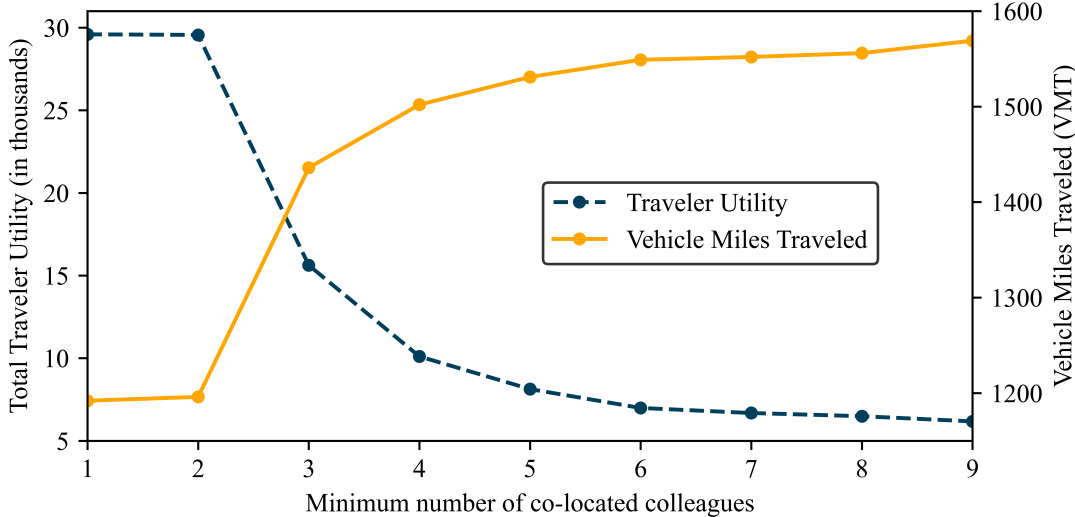
Figure 6: Sensitivity of total traveler utility and VMT to changes in the number of colleagues that must be co-located

The second associate dependency is a soft dependency where team members are incentivized (but not required) to co-locate with one another. Travelers with flexible destinations were divided at random into teams of constant size. Co-locating two team members results in a bonus payment of u^{max} to the operator. The maximum solution time for these experiments was 10.3 seconds. Figure 7 shows how the number of co-located team members increases with u^{max} for various team sizes. Even small values of u^{max} can increase the number of team members working at the same location. For 15 person teams, the number of employees working with another team member increases from an initial 44 to 53 when $u^{\mathrm{max}} = 2.5\$$.

Figure 8 presents profit and VMT for increasing values of u^{max} when the team size is fixed to 15 people. Like in Figure 7, the effect of the co-location bonus plateaus after \$2.50
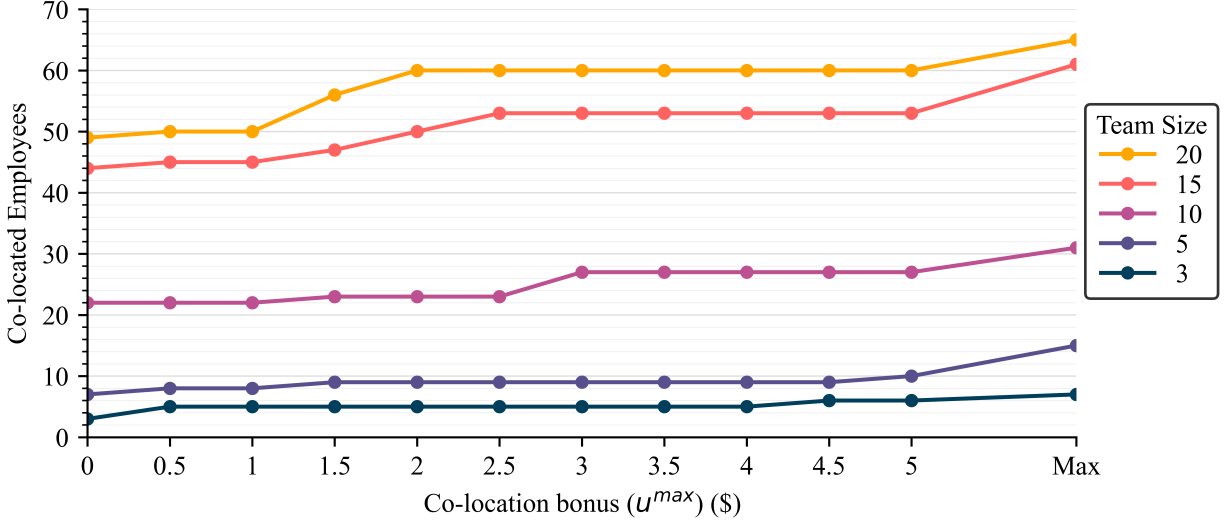
Figure 7: Sensitivity of the number of co-located employees to changes in the associate benefit $u^{\max}$ for a range of team sizes

for teams of 15 people; VMT and profit (without co-location bonus) are largely unchanged as the bonus grows from \$2.50 to \$5.00. There is an empirical upper bound for the number of co-located employees, as travel costs make it very unlikely for certain team members to travel to the same destination. While the total profits increase due to the addition of $u^{\max}$, the profits earned directly from passengers (profit without bonus) decreases when the incentive for co-location outweighs the incentive to operate the most profitable trips. Similar to the trends observed in Figure 5 where the location capacity constraint is applied, there is also a rise in VMT when co-location is heavily incentivized due to the additional travel required.

6. Policy implications

The experimental results show that, given the conditions described in Section 5.1, remote work policies can improve ride-pooling adoption rates and profits while reducing VMT. While the performance increases from destination flexibility may seem somewhat low, note that the experiment covers only people who live and work in a very small geographic area (Manhattan). Flexible ride-pooling platforms serving an entire urban region with medium and long-distance commutes could have an even larger impact. Location capacity constraints,
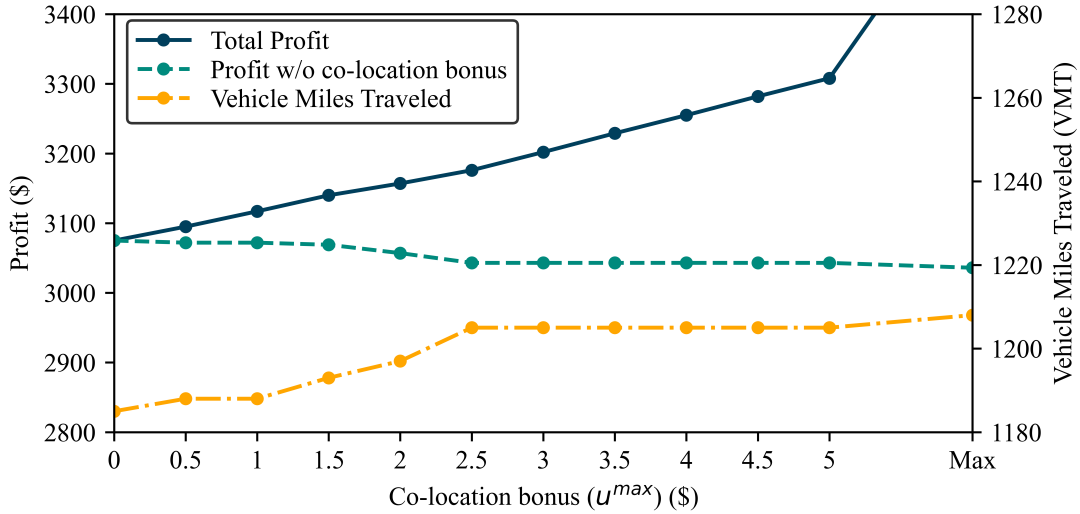
Figure 8: Sensitivity of total profit, profit without benefit and VMT to changes in the associate benefit $u^{\max}$

co-location constraints and co-location incentives are found to temper the travel benefits of flexible destinations by requiring or encouraging travel to suboptimal locations. This research has implications for three different remote work stakeholders: employers, policy makers and mobility services.

Employers considering remote work policies can use the tools presented in this study to evaluate different remote work policies and real estate portfolios. There is an ongoing tension between employers who prefer for their staff to have face-to-face interactions and remote workers who would prefer to avoid the costs of traveling to the workplace. This study shows that allowing more employees to work from multiple locations (e.g. co-working spaces) reduces VMT and improves traveler utility, even if co-location of team members is desired. Having a large portfolio of possible work locations spread across an urban region is also helpful in limiting travel costs for employees and avoiding transportation-related externalities. Ensuring that the most easily accessed locations have sufficient capacity will allow employees to take advantage of nearby flexible work locations.

Given that flexible work locations have the potential to reduce VMT through increased ride-pooling, policy makers should consider how to encourage mobility operators to offer these features. Furthermore, flexible work location policies could be considered as part of a larger

travel demand management program. Land use policies that allow for new collaborative workplaces in residential areas may also reduce the distance that remote workers need to travel when they choose to do remote work outside the home.

These results demonstrate that ride-pooling platforms could leverage the tools described herein to provide more efficient matching and greater adoption of pooled rides by allowing customers to enter multiple possible destinations for the same trip. Furthermore, future ride-pooling platforms could allow two friends or colleagues leaving from different origins to choose a central location for a meeting or social event based on some mutual combination of travel costs and destination preferences. Such features would extend existing ride-pooling platforms to more of a comprehensive trip planning platform. Some have predicted that shared autonomous vehicles may eventually gain a substantial market share (Narayanan et al., 2020); in such an environment, the efficiency gains from flexible destination ride-pooling could have a significant impact on overall travel demand. Platform operators could also create new business models by partnering with employers and co-working spaces to provide integrated mobility and workplace solutions for the future of work.

7. Conclusions

This paper establishes a vocabulary and framework for modeling travel demand and supply optimization in the context of remote work. The framework is used to study the impacts of flexible remote work locations on ride-pooling outcomes. A new ride-pooling matching model is proposed with linear formulations that capture the dynamics of work location choice for the first time, including location capacities and the benefits of co-locating with colleagues. These formulations are tested using real demand, demonstrating the impacts of remote work dependencies and the tractability of the model formulations. While the model is applied to shared ride-pooling in this paper, the methods can be easily modified for passenger-vehicle matching with other shared mobility modes such as demand-responsive transit by changing the vehicle passenger capacity and removing any exclusive rides from

the set of possible trips.

This work extrapolates from current trends in order to provide high-level insights for a possible future. Real data was used wherever possible, but several assumptions were necessary to model travel behaviors and employment scenarios in the context of remote work. Surveys are needed to quantify travel preferences and employer plans regarding flexible work locations in order to improve the destination utility assumptions. Another limitation of the case study is that it compares a ride-pooling service with some flexible destinations against a ride-pooling service with no flexible destinations for a single period of operations that assumes a fixed number of customers and drivers. Given that flexible destinations are shown to improve operational efficiency, operational profitability and utility for customers, more drivers and passengers may be attracted to the platform over time (Wilkes et al., 2021). Future research in this area could extend the modeling framework to a day-to-day simulation of ride-pooling operations with flexible destinations.

Other potential extensions of this research include developing multi-objective models to design remote work policies that balance travel utility and productivity. This could include a more sophisticated, graph theory-based approach to productivity modeling, where productivity is related to the presence of co-workers and random interactions between different organizations. Such interactions do not need to be random or exclusive to the workplace; future research could also include the design of a ride-pooling algorithm that matches agents strategically in order to promote idea flow.

8. Acknowledgements

9. Author Contribution Statement

The authors confirm contribution to the paper as follows: study conception and design: N.S. Caros, J. Zhao; data collection: N.S. Caros; analysis and interpretation of results: N.S. Caros, J. Zhao; draft manuscript preparation: N.S. Caros, J. Zhao. Both authors reviewed the results and approved the final version of the manuscript. The authors do not have any conflicts of interest to declare.

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