

The impact of trip density on the fleet size and pooling rate of ride-hailing services: A simulation study

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Abstract

Several trends, such as digitalization and advancements of autonomous driving technologies, have led to large investments and a strong expansion of app-based ride-hailing services in recent years. In this study, simulation experiments are carried out for two regions in Germany: the metropolitan Berlin area and the rural area of the district Vulkaneifel (Volcanic Eifel). Transport users' travel behavior is fixed and the operator is enabled to adjust the ride-hailing vehicle fleet size to keep 90% of all waiting times below 10 minutes. The results show that the trip density has a major impact on the required ride-hailing fleet size as well as the resulting service (e.g. operation hours, vehicle-kilometers and pooling rate). The simulation results reveal a nonlinear relationship of trip density and ride-hailing service parameters. A linear upscaling of simulation results for a small population sample may yield an overestimation of the fleet size, operating hours and vehicle kilometers. For low trip densities, the effect of pooling (ride-sharing) is disproportionately smaller compared to larger trip densities.

Keywords: agent-based simulation; ride-hailing; shared autonomous vehicles (SAV); trip density; demand responsive transit (DRT); MATSim

1 Introduction and problem statement

Several trends, such as digitalization and advancements of autonomous driving technologies, have led to large investments and a strong expansion of App-based ride-hailing services in recent years. In some cities or regions, ride-hailing operators, e.g. UBER and Lyft, play an essential role in mobility provision.

The Mohring effect describes that an increase in public transit demand typically yields an increase in public transit supply, e.g. an increase in bus frequency, which then decreases waiting times for all public transit users (Mohring, 1972). For road congestion, an opposite effect is observed: Higher demand levels increase travel times for all road users, and even if road capacities are expanded road users are not better off. The Mohring effect is typically only discussed in the context of conventional public transit services, in particular schedule-based services. The present study addresses the Mohring effect in the context of ride-hailing services: An increase in travel demand requires a larger fleet of ride-hailing vehicles. This in turn improves the availability of vehicles and may reduce waiting times for all ride-hailing users. Operators of such services may use these positive economies of scale by limiting the ride-hailing service to high demand areas. Ride-hailing services with ride-sharing (pooling) also allow for more flexibility in the dispatching and trip insertion algorithms. This provides a further incentive for operators to rather provide services in densely populated areas and once more raises the question of how to deal with sparsely populated regions.

In several studies, ride-hailing services are simulated for a fixed travel demand (Maciejewski and Bischoff, 2015; Bischoff and Maciejewski, 2016; Bischoff et al., 2018; Nagel et al., 2018; Bischoff, 2019). Most of these studies address the mechanics of the dynamic vehicle routing problem, e.g. waiting times resulting from different vehicle fleet sizes (Maciejewski and Bischoff, 2015) or rebalancing algorithms (Bischoff and Maciejewski, 2020). In some studies, ride-hailing services are investigated for different predefined trip densities (Yan et al., 2020). In other studies, mode choice behavior is explicitly taken into consideration (Kaddoura et al., 2020a; Zhao and Kockelman, 2018; Kaddoura et al., 2020b; Hörl et al., 2019). In most of these studies, agents individually maximize their expected utility and adapt to the transport supply including the ride-hailing service. The agent-based simulation framework MATSim (Multi-Agent Transport Simulation, see www.matsim.org) (Horni et al., 2016) allows for a detailed simulation of ride-hailing services as well as conventional modes of transportation. For the adaptation of demand to supply, an evolutionary iterative approach is applied which requires simulation times of several days. To improve computational performance a common approach (Horni et al., 2016, see e.g. Part IV “Scenarios”) is to use a population sample,

e.g. a randomly chosen subset of agents which contains 25%, 10% or for draft studies even 1% of the real-world population. At the same time, simulated road capacities are reduced by the same fraction to fix the ratio of demand and supply and to account for traffic congestion. Results such as traffic volumes are then typically up-scaled to the full population. For demand levels, the up-scaling is straightforward, e.g. for a 10% sample one agent represents 10 travelers. In contrast, for other parameters such as resulting ride-hailing vehicle fleet sizes or pooling rates, the demand density plays an important role which does not allow for a simple proportional up-scaling to the 100% population.

This study addresses synergies between ride-hailing users and required fleet sizes for different demand levels. At the same time, this study answers questions regarding different population samples and the up-scaling of simulation results.

2 Methodology: Simulation framework

The simulation experiments carried out in this study use the agent-based and dynamic transport simulation framework MATSim (Multi-Agent Transport Simulation, see www.matsim.org) (Horni et al., 2016). In MATSim, travel demand is simulated as individual agents who have a physical and cognitive behavior. An agent’s intended behavior for a specific day is described by a travel plan which consists of an activity-trip-chain, including the modes of transportation, departure times and the route. All agents individually execute their daily travel plans and the mobility behavior is simulated. Agents compete for the same transport resources and interact with each other. Both private cars and ride-hailing vehicles interact on the road network applying a queue model with spill-back effects.

The simulation of ride-hailing services is based on an existing module for dynamic vehicle routing problems (Maciejewski, 2016; Maciejewski et al., 2017) and the Demand Responsive Transit (DRT) module (Bischoff et al., 2017). A simulated ride-hailing trip includes the following steps: (1) An agent first walks to the next road segment or virtual stop inside the service area. (2) The agent requests a ride. (3) The trip request is considered in the vehicle-customer dispatching: The trip is assigned to the next available vehicle or in case the ride-hailing system operates at capacity limit and trip requests cannot be served within the predefined service quality criteria, the request is assigned to the vehicle causing the least additional operation time. With ride-sharing (pooling), the dispatch and insertion algorithm also accounts for predefined service quality parameters for the passengers that are already scheduled to use the same vehicle. (4) The ride-hailing user waits for the vehicle to

arrive and then enters the vehicle. (5) The user arrives at the destination road segment or virtual stop, gets off the vehicle and walks to the destination activity.

To keep waiting times at a constant level, i.e. to provide a certain predefined service quality, the vehicle fleet size is dynamically adjusted during the simulation experiment. A proportional controller is used which randomly clones or removes vehicles from one iteration to the next one. A more detailed description of the applied vehicle fleet adjustment approach is provided in Kaddoura et al. (2020c).

3 Simulation experiments

3.1 Case studies

In this study, simulation experiments are carried out for two regions in Germany: the metropolitan Berlin area and the rural area of the district Vulkaneifel (Volcanic Eifel). For each case study, the activity-based transport model is provided as an excerpt from the nation-wide MATSim model of Germany by Senozon Deutschland GmbH (www.senozon.com). The road network and activity facilities, e.g. schools, are based on OpenStreetMap (www.osm.org). The synthetic population is generated using regular traffic surveys and anonymized mobile phone data. For an in-depth information of the applied demand generation methodology, in particular the Mobility Pattern Recognition, see (Neumann and Balmer, 2020).

Ride-hailing service in the eastern inner-city area of Berlin, Germany The population includes all persons with an age of 14 or more years that travel from, to or through the area of interest. In a previous simulation experiment, transport users were enabled to generate their choice sets by choosing between private car, public transit, bicycle, ride, walk and/or ride-hailing mode. The ride-hailing service area is set to the eastern part of the inner-city Berlin area. The resulting mode choice behavior and departure times are fixed and used as input for the simulation experiments carried out in this study. The total trip number amounts to 753,864 ride-hailing trips (upscaled to the 100% population sample). The spatial distribution of the trip density for the ride-hailing mode is shown in Fig. 1a.

Ride-hailing service for school children in the Volcanic Eifel, Germany This case study is limited to people below the age of 19 years. For all agents with at least one school activity (primary,

secondary or tertiary education) in the Vulkaneifel district and with a direct trip from home to school in the morning, the trip mode is changed to the ride-hailing mode for all trips (including the trips in the afternoon) that meet the following conditions: (i) the trip starts and ends within the Vulkaneifel area, (ii) the euclidean distance between trip origin and destination is at least 2 km. The departure time for the trip from home to school in the morning is set according to the required departure time when using public transit assuming a desired arrival time at school of 7.30 a.m. in Daun and 8.00 a.m. for the rest of the Vulkaneifel. The total trip number amounts to 8,372 ride-hailing trips (100% population sample). The spatial distribution of the resulting ride-hailing trip density is shown in Fig. 1b.

3.2 Simulation setup

For the Berlin case study, simulation experiments are carried out for a 5%, 10%, 15%, 20% and 25% population sample. For the Vulkaneifel case study, simulation experiments are carried out for population samples from 10% up to 100%. Road capacities are reduced accordingly in each simulation experiment. Transport users' travel behavior is fixed and the operator is enabled to adjust the ride-hailing vehicle fleet size over several hundreds of iterations with the objective to keep 90% of all waiting times below 10 minutes. The ride-hailing service provides a door-to-door service with pooling (ride-sharing) of up to four passengers. In this study, there is no repositioning of empty vehicles (rebalancing). The ride-hailing operator is forced to serve all ride requests, that is, there are no trip rejections.

4 Results and discussion

The simulation experiments for both the Berlin and Vulkaneifel case study, show structurally similar results. Fig. 2 provides an analysis of the required ride-hailing vehicle fleet size for both the Berlin and Vulkaneifel case study. A larger population sample translates into a higher demand level and therefore a larger required vehicle fleet to keep a constant level of service quality. However, for larger sample sizes, the number of additionally required vehicles decreases. An explanation for this is that a higher demand density yields a larger fleet size which allows for more flexibility in the operator's dispatching and pooling. With shorter spatial and temporal intervals between requests, pick-up times are reduced and pooling works much better. Applying a proportional upscaling factor (e.g. 10 for 10% sample, 4 for a 25% sample) reveals a nonlinear slope of the upscaled vehicle fleet

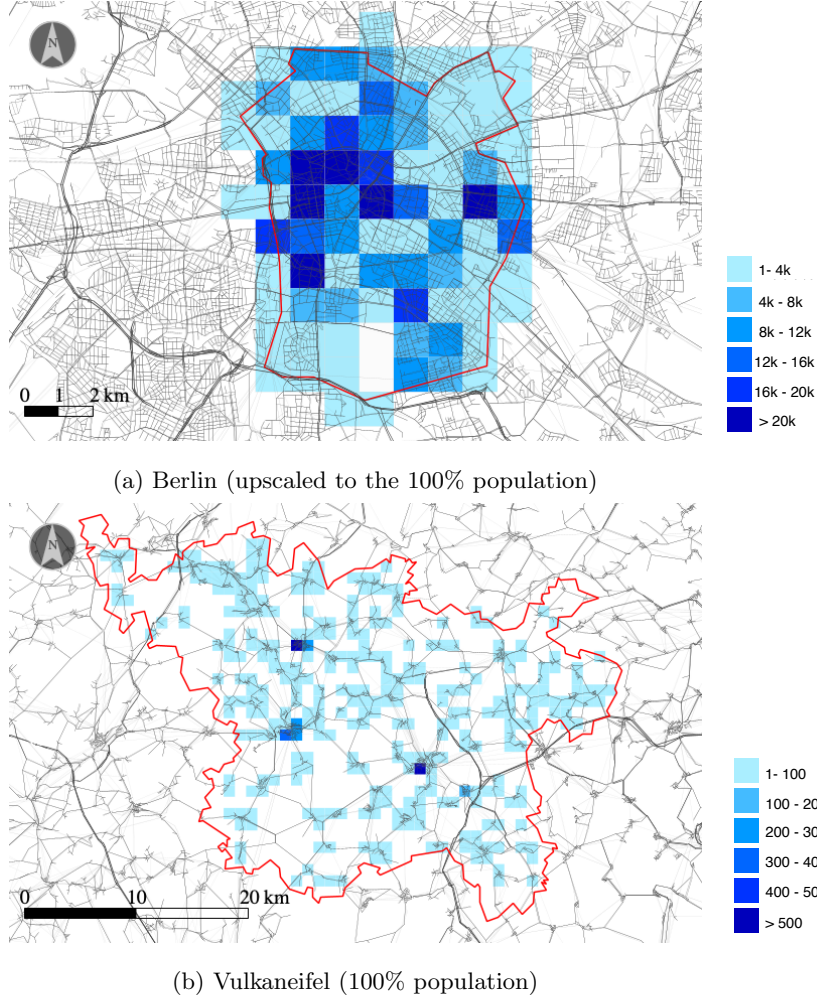


Figure 1: Ride-hailing trip density (in trips per km^2 by trip origin); the red line marks the ride-hailing service area

size (see Fig. 2a and Fig. 2c), with a very strong decrease in required ride-hailing vehicles for small population samples and a rather small decrease for larger population samples of above approximately 20%. Fig. 2b and Fig. 2d depict the proportional (red) and corrected (blue) upscaling factors based on the simulated fleet sizes and a normalization for the 100% population sample. The non-linear regression analysis reveals that the corrected upscaling factor as a function of sample size is about the same in both the Berlin and Vulkaneifel case study. Tab. 1 provides further relevant upscaling factors for the operating hours and vehicle-kilometers traveled.

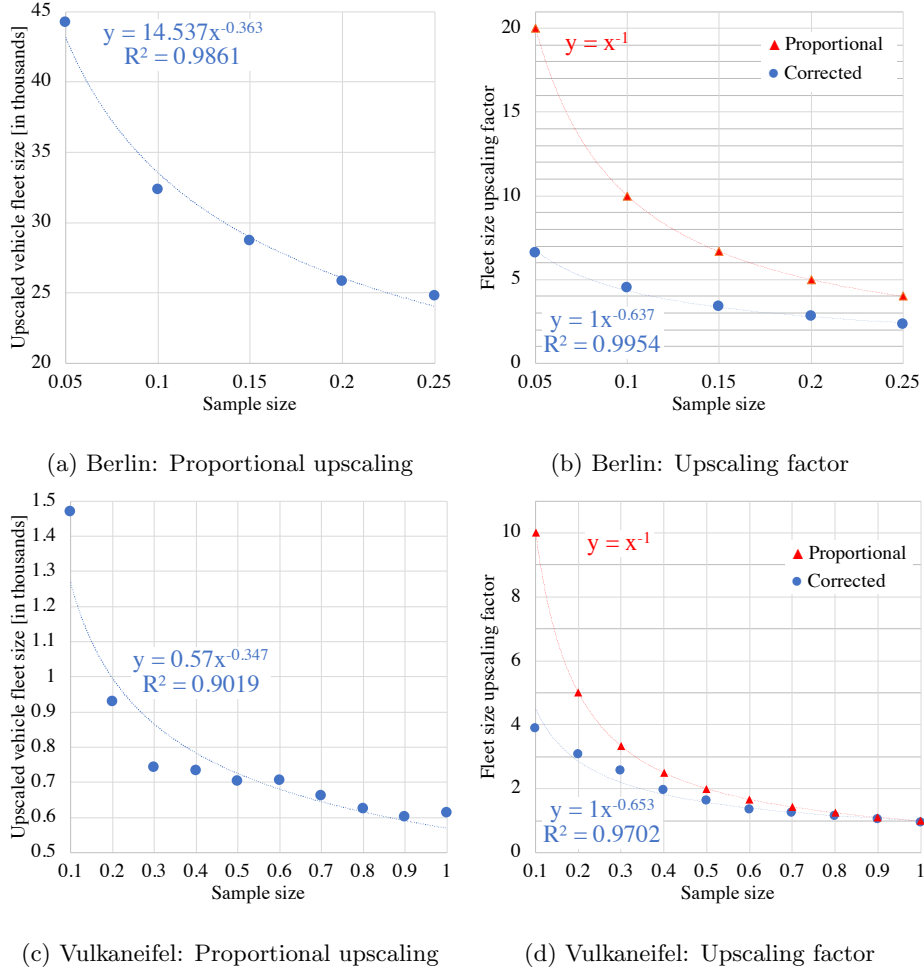


Figure 2: Simulation results: Proportionally and corrected upscaling of the ride-hailing vehicle fleet size

A further observation is that a larger population sample increases the effect of pooling. Fig. 3 shows the ratio of revenue distance to total distance where revenue distance describes the direct passenger-km without the extra kilometers for detours to pick up additional passengers. As the demand is fixed, a higher value for the revenue distance ratio means that pooling can be performed more often and more efficiently (without violating any service provision constraints). For the densely populated Berlin area, even for very small population samples, the ratio is above 100%. For the less densely populated Vulkaneifel, small population samples yield a ratio below 100% which means that the pooling effect does not compensate for the additional vehicle-kilometers caused by pick-up trips.

Table 1: Corrected upscaling factors as a function of sample size x based on a non-linear regression with $x = 0.05, 0.1, \dots, 0.25$ for Berlin and $x = 0.1, 0.2, \dots, 1.0$ for Vulkaneifel

	Berlin	Vulkaneifel
Ride-hailing fleet size	$x^{-0.637}$ ($R^2 = 0.9954$)	$x^{-0.653}$ ($R^2 = 0.9702$)
Ride-hailing operating hours	$x^{-0.662}$ ($R^2 = 0.9975$)	$x^{-0.769}$ ($R^2 = 0.9949$)
Ride-hailing vehicle-kilometers	$x^{-0.928}$ ($R^2 = 0.9999$)	$x^{-0.856}$ ($R^2 = 0.9996$)

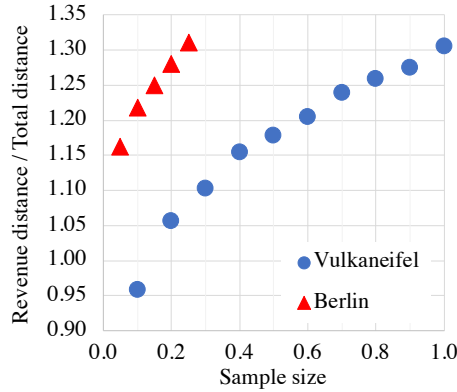


Figure 3: Revenue distance ratio

This is also evident in Fig. 4, where it is shown how ride-hailing vehicles are occupied throughout the day. For the larger population samples, the gray area becomes smaller which means that the proportion of waiting vehicles declines. Also, for larger population samples the proportion of vehicles with more than one passenger increases, in particular during peak times.

The impact of traffic congestion To investigate the impact of traffic congestion, the simulation experiments for Berlin described above are repeated for a modified road network with increased capacities to eliminate any form of traffic congestion. The resulting vehicle occupancy in the uncongested case is shown in Fig. 5. The results show a significant reduction of the number of required ride-hailing vehicles. Also, throughout the day, the number of waiting vehicles has been significantly reduced. During peak times, even *all* vehicles are en route, either picking up passengers or being occupied by one or more passengers. Nevertheless, the fleet is large enough to maintain the specified quality of service.

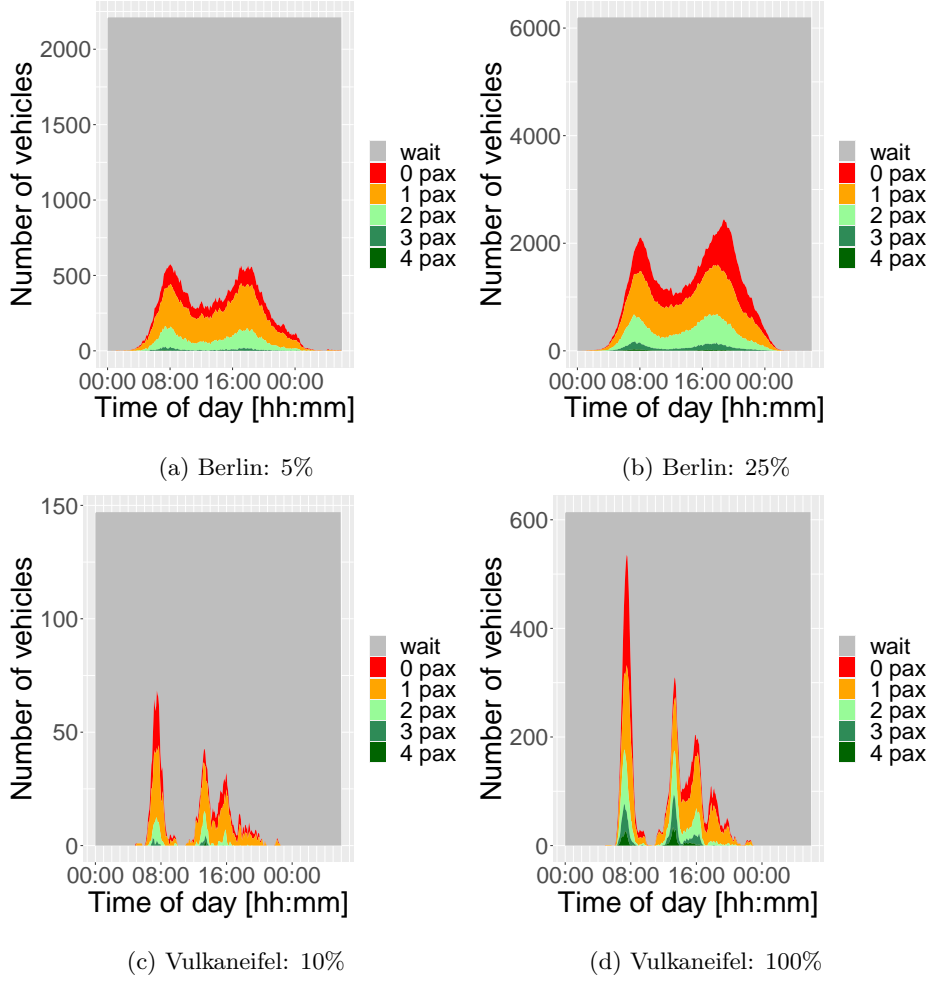


Figure 4: Vehicle occupancy

Further discussion In this study, for each fixed demand level, the ride-hailing fleet size is adjusted to obtain a constant service quality throughout all simulation experiments. An alternative study design is to allow for mode choice and provide a fixed ride-hailing fleet size which is set proportionally to the sample size in each simulation experiment. The simulation results in this study, in particular Fig. 2, indicate that for small population samples and small numbers of simulated ride-hailing vehicles, the service quality is too poor and therefore ride-hailing demand levels may be underestimated.

In the present study, idle vehicles remain at the drop-off location if no passenger is on board until they are reassigned to the next request. Vehicle rebalancing has the effect of an increased empty

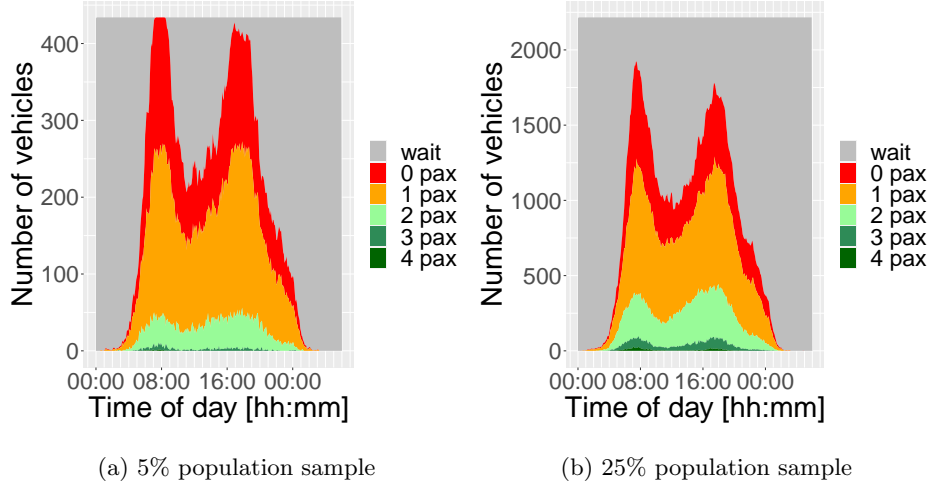


Figure 5: Berlin (uncongested scenario): Vehicle occupancy

mileage but may improve the service level, (Bischoff and Maciejewski, 2020; Schlenther et al., 2020; Hörl et al., 2017). That is, fewer vehicles are required to provide the same waiting times and vehicles have a higher occupancy ratio. Depending on the rebalancing strategy (demand-anticipatory versus supply-anticipatory, a mix or any other form, (Winter et al., 2020) the trip density may have an impact on the rebalancing efficiency and vice-versa. A more detailed investigation of the demand reaction to a variety of rebalancing strategies is provided in (Schlenther et al., 2020).

5 Conclusion and outlook

The results have shown that the trip density has a major impact on the required ride-hailing fleet size as well as the resulting service (e.g. operation hours, vehicle-kilometers and pooling rate). The simulation results confirm the nonlinear relationship of trip density and ride-hailing service parameters. A linear upscaling of simulation results for a small population sample may yield an overestimation of the ride-hailing vehicle fleet size, operating hours and vehicle kilometers. This will have a crucial effect on the cost calculation yielding too high cost levels. Another observation is that for small population samples, the effect of pooling (ride-sharing) may be underestimated when directly transferring results to the full population.

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