Highlights:

- Fieldwork and semi-structured interviews identify additional labor roles for robotaxis
- Labor remains a significant operational cost for existing robotaxi services
- Robotaxi operating costs are still lower than those of traditional taxi services
- Utilization rates and annual mileage will be limiting factors for robotaxi competitiveness
- Shift from taxi to robotaxi services could decrease the total number of frontline jobs

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Modeling the Operational and Labor Costs of Autonomous Robotaxi Services

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Data Accessibility

The code and data used in this study and a detailed supplementary information document are available at https://github.com/lkaplan25/av_labor_cost_2024

Competing Interests

Declarations of interest: none

Abstract

Autonomous vehicle (AV) companies are rolling out driverless taxi-type services in cities around the world, promising to enhance road safety, promote equity, and foster environmental sustainability while simultaneously threatening the jobs of current taxi and ride-hailing drivers. The potential impacts of these "robotaxi" services hinge upon not only whether AV technology becomes sufficiently performant, but also whether AV services become economically competitive. In this study, we develop ground-up cost models for a traditional taxi and a robotaxi service to compare their relative competitiveness. We draw on direct observations of commercially available robotaxi services, semi-structured interviews with AV operational and regulatory experts (N = 27), and archival documents to include the most detailed accounting of frontline robotaxi labor roles to date. We find that labor remains a significant cost for existing robotaxi services but that robotaxi operating costs are still lower than those of traditional taxi services. Ultimately, utilization rates and annual mileage will serve as the most influential factors for robotaxi competitiveness. Finally, if jobs shift from traditional taxi to robotaxi services, the total number of frontline jobs could decrease by between 57% to 76%, but the distribution of worker wages would shift higher. Transportation planners, researchers, and policymakers should continue accounting for labor costs in an AV future, as these costs will influence where AV deployment and job losses are (and are not) likely to occur, and should proactively investigate alternative career paths for potentially displaced frontline workers. Robotaxi costs are highly sensitive to lower labor ratios (i.e., fewer vehicles per worker), but firms reach economies of scale relatively quickly. Robotaxi firms should weigh marginal labor cost reductions against impacts to passengers and workers.

Keywords: Autonomous vehicles; robotaxis; automated taxis; cost model; labor

Declarations of interest: none

1 Introduction

Autonomous vehicle (AV) companies are rolling out driverless taxi-type services (robotaxis) in cities around the world, including in multiple cities in the United States. These firms have attracted billions of dollars of investment, with financial backers betting on a future in which vehicle automation could cut labor costs and increase profitability via removal of the driver (Shetty, 2020). Indeed, labor is one of the main cost expenditures for current taxi operators (Daus, 2023).

Investors are not the only group eager for an AV future. Many cities are looking to AVs to make their transportation systems cheaper, safer, less congested, and more accessible (McAslan et al., 2021). Prior studies find that robotaxis could improve road safety (Blumenthal et al., 2020), decrease congestion by reducing the number of vehicles required to meet demand (Hamadneh and Esztergár-Kiss, 2021), enhance fuel efficiency via more efficient driving and braking (Williams et al., 2020), and offer new mobility pathways for low-income and low-mobility populations if designed appropriately (Creger et al., 2019; Steckler et al., 2021). Across various stakeholder groups including users, legislators, operators, and manufacturers, safety ranks as the most important issue related to potential AV deployment (Hamadneh et al., 2022), though user costs will also influence adoption (or lack thereof) of AVs (Stoiber et al., 2019).

Balanced against these hopes is significant concern for the impact of AVs on labor (Cohen et al., 2018; Hilgarter and Granig, 2020; Norton et al., 2021). One recent study estimated that vehicle automation could eliminate 1.3 to 2.3 million workers' jobs over the next 30 years (Groshen et al., 2018). While many of the at-risk jobs are in the trucking sector, AVs still pose a potential threat to taxi and ride-hailing drivers' jobs. In the United States, there are an estimated 395,700 taxi drivers, shuttle drivers, and chauffeurs, and over 830,000 jobs in the broader door-to-door passenger transportation service sector (Bureau of Labor Statistics, 2023a; Cameron, 2020). Critically, many of these driver roles are filled by immigrants who may face greater challenges recovering from job displacement (Dubal, 2017).

In this study, we investigate potential competition between traditional taxi and robotaxi services with the aim of contributing to discussions on potential AV labor impacts. We develop ground-up cost models for both types of services, and are the first study to ground our labor assumptions in data on the operations of currently-deployed robotaxi services in the U.S. We exclude direct analysis of autonomous ride-hailing services as the structure of existing robotaxi firms more closely mirrors that of a centralized taxi company rather than a decentralized (with regard to frontline workers) Transportation Network Company (TNC, e.g., Uber). Moreover, Negro et al. (2021) find that vehicle automation largely does not impact TNCs' operating costs. While competition from robotaxis could still impact the jobs of ride-hailing drivers, the cost dynamics by which that competition may arise are beyond the scope of this study. To further unpack potential labor impacts, this study also offers estimates regarding the number of frontline workers required to support traditional taxi and robotaxi services and their associated wage distributions.

2 Prior literature on robotaxi costs

Multiple prior studies have considered the costs of AVs. Some researchers have highlighted the different types of costs borne by road users and categorized these costs in terms of direct vs. indirect costs, tangible vs. intangible costs, and internal vs. external costs (Labi et al., 2023). While cities and transportation planners need to account for externalized costs such as traffic congestion impacts and air quality, private fleet operators are most concerned with the direct operational costs that impact their economic competitiveness. Within the domain of operational costs, researchers have estimated the potential costs of different AV services (Table 1).

Multiple prior studies have modeled the costs of different AV services (**Table 1**). Burns et al. (2012) proposed one of the earliest estimates, finding that a system of shared robotaxis in Manhattan could provide transportation services at a cost of $0.40/mi. Additional studies have similarly estimated that autonomous taxi and ride-hailing services would outcompete their non-autonomous counterparts (Compostella et al., 2020; Greenblatt and Saxena, 2015; Wadud, 2017). Fulton et al. (2017) described how a combination electrification and automation could decrease system operational costs by 40%. From the consumer perspective, a report from UBS Global Research (2017) posited that cost savings from robotaxi operations could decrease fares by as much as 80%, dramatically shifting mode preferences.

Though cost estimates have become more detailed over time, they still lack precision in two key areas: 1) the capital cost of autonomous vehicle technology, and 2) the labor costs to operate an AV service. Critically, these two forms of fixed asset expenditures account for the majority of costs in conventional modes (Negro et al., 2021).

The capital cost of AV technology is highly uncertain, with prior estimates ranging from $2,700 to $50,000 per vehicle (Burns et al., 2012; Fagnant and Kockelman, 2016; Greenblatt and Saxena, 2015; Stephens et al., 2016). Many studies either provided no details regarding this assumed cost or generally discussed high upfront investment costs that will decrease over time (Arbib and Seba, 2017; Johnson, 2015; UBS Global Research, 2017). The majority of studies used an automation cost of around $10,000 per vehicle, which originates from a 2015 Boston Consulting Group report and is based on Tesla's original proposed cost for its "full self-driving" sensor suite (Bauer et al., 2018; BCG, 2015; Bösch et al., 2018; Compostella et al., 2020; Fulton et al., 2017; Hazan et al., 2016; Johnson and Walker, 2016; Nunes and Hernandez, 2020; Sperling et al., 2018; Stephens et al., 2016; Wadud, 2017). Notably, Tesla's suite does not include LiDAR sensors, which many experts believe are essential for safe AV operations and are used in all commercially-available robotaxi services (Bauchwitz and Cummings, 2022; Cruise, 2023a; Waymo, 2023; ZF, 2023). While LiDAR costs have decreased significantly and will undoubtedly continue to decline, top-of-range LiDAR sensors still cost approximately $5,000 each (Korosec, 2019). Current robotaxis rely on multiple LiDAR sensors, dozens of other sensors, and on-board computing equipment to achieve critical autonomy and mapping functions (Rodnitzky, 2022). It is unclear when, or if, AV capital costs might actually reach prices akin to prior studies' assumptions. In this study, we utilize AV prices that reflect current AV capital costs in order to look at nearer-term competition, and consider lower technology costs as part of our scenario analysis.

A second common assumption is that vehicle automation will "zero out" labor costs by removing the driver (Arbib and Seba, 2017; Compostella et al., 2020; Fulton et al., 2017; Greenblatt and Saxena, 2015; Johnson and Walker, 2016; Sperling et al., 2018; UBS Global Research, 2017). More recent studies have included some labor costs for AV services. Wadud (2017) and Wadud & Mattioli (2021) accounted for some labor expenditures by decreasing former driver costs by 60% for AV services to capture other roles that may arise and Bauer et al. (2018) similarly included a $2.50 per vehicle-day general administrative overhead expense. Bösch et al. (2018) and Becker et al. (2020) noted that labor expenses for robotaxis will shift from drivers to higher cleaning costs as customers may sully or damage vehicles more often absent social pressure from a driver. Nunes and Hernandez (2020) were the first to consider emerging labor roles in their model, adding in costs for AV safety oversight monitors (Heineke et al. (2022) also mentioned remote AV workers but provided no cost details). Negro et al. (2021) offered the most detailed inclusion of labor to date, including safety oversight monitors, general fleet maintenance personnel, and administrative staff members. Their model, however, still relies on assumptions, rather than actual operational practice, about required labor roles. In this study, we improve the precision around labor cost estimates with an up-to-date understanding of the labor roles needed to support robotaxi services.

Table 1: Summary of prior cost estimates, including assumed technology costs and labor considerations. VMT = vehicle miles traveled, PMT = passenger miles traveled.

Paper	Units	Cost	Technology estimate	Labor Considerations
Burns et al. (2012)	$/VMT	$0.40	$6,935*	NA
Johnson (2015)	$/VMT	$0.12-0.29	NA	NA
Greenblatt and Saxena (2015)	$/VMT	$0.30-0.50	$5,000 (2030)	Eliminate driver costs for AVs
Boston Consulting Group (2015)	NA	NA	$10,000	NA
Stephens et al. (2016)	$/PMT	$0.28-$0.55	$2,700-$10,000	NA
Fagnant and Kockelman (2016)	NA	NA	$50,000	NA
Johnson and Walker (2016)	$/VMT	$0.08	$2,700 (2035) - $10,000 (2025)	Eliminate driver costs for AVs
Hazan et al. (2016)	$/PMT	$0.15	$10,000	NA
Arbib and Seba (2017)	$/VMT	$0.06-0.24	NA	Eliminate driver costs for AVs
Wadud (2017)	$/VMT	$1.01	$16,000	Decreases driver costs by **60%** for AVs to account for other roles (e.g., back office infrastructure, ensuring safety) - max scenario decreases labor costs by 80%
Fulton et al. (2017)	$/PMT	$0.68	$10,000 (2030)- $5,000 (2040)	Eliminate driver costs for AVs but include overhead costs of operating a ride-hailing service for the shared AV/EV fleet
UBS Global Research (2017)	NA	NA	NA	Eliminate driver costs for AVs
Bösch et al. (2018)	$/PMT	$0.66	$7,000**	Costs for autonomous taxis will shift from paying drivers to higher cleaning costs
Bridges (2018)	$/VMT	$0.06-0.24	NA	NA
Sperling (2018)	$/PMT	$0.10-0.20	$10,000	Eliminate driver costs for AVs
Bauer et al. (2018)	$/VMT	$0.29-$0.61	$10,000	$2.50 per vehicle-day ("administrative overhead")
Becker et al. (2020)	$/PMT	$0.10-$0.71	$5,000	Include cleaning and fixed overhead costs
Compostella et al. (2020)	$/VMT	$0.36-0.41	$10,000***	Eliminate driver costs for AVs
Nunes and Hernandez (2020)	$/VMT	$1.58-$6.01	$15,000	Include safety oversight for robotaxis at varying vehicle to worker ratios
Negro et al. (2021)	$/VMT	$0.76-$0.84	$40,000	Include safety oversight for robotaxis, fleet maintenance personnel, and administrative staff
Wadud and Mattioli (2021)	$/VMT	$0.68-$0.83	~$3,800****	Based on Wadud (2017) taxi labor costs
Heineke et al. (2022)	NA	NA	NA	Discuss vehicle control center, no cost provided
Litman (2023)	$/VMT	$0.50-$1.00	NA	Discusses potential need for other types of onboard workers, not included in cost comparison

NA indicates that information about the given variable was not provided.
*Assuming cost of $19 per day; **Automation will increase vehicle price by 20%. Assuming price value for midsize vehicle
***Assuming $30,000 for high-cost scenario.; ****Converted from British pounds

3 Methods

We develop ground-up cost models for a non-AV taxi service and a robotaxi service, grounding our analysis in data on current robotaxi operations in U.S. cities and existing taxi operations. We test assumptions regarding operations of robotaxi services via a baseline scenario and four alternative scenarios, and use Monte Carlo simulation to account for both uncertainty and variation in our model inputs (e.g., differences in demand based on time of day or time of year). All models are built in the R programming language (R Core Team, 2024) and all code is publicly available at [link removed to protect anonymity during review].

3.1 Identifying Labor Roles

We investigate firms operating robotaxi services in the U.S. to gain early insights into the "frontline" labor roles (i.e., those that directly support the service rather than those involved in the technology design and development) necessary to support these services and the current wages for those roles. We use multiple data sources to triangulate information about current labor roles, including direct observations, interviews, and a variety of archival data sources (**Table 2**).

One of the authors conducted direct observations of two different firms' commercially-available robotaxi services in the U.S. (N = 13 rides), as well as six hours of observation of a robotaxi command center and two hours of observation of a robotaxi fleet maintenance depot between July 2022 and August 2023. Five of the robotaxi rides included a human safety driver onboard while the remainder did not. Over the course of the rides, the researcher interacted with customer-facing employees of the service, including forms of human remote support.

To supplement these observations, the same researcher conducted semi-structured interviews with AV operational and regulatory experts (N = 27). Interviewees were selected via purposive sampling to capture the different types of frontline roles involved in robotaxi services and to cover different perspectives (Eisenhardt and Graebner, 2007). Over half of the interviewees were either current or prior employees of a commercial robotaxi company. Interviews were conducted until theoretical saturation was achieved (i.e., new interviewees did not mention any new labor roles, and previously observed roles were mentioned multiple times across different interviewees) (Eisenhardt, 1989; Szajnfarber and Gralla, 2017). Observations and interviews were conducted with approval from the Institutional Review Board at the authors' institution. All interviews for which consent to record was given were recorded and transcribed via auto-transcription software within 24 hours of the interview. All transcripts were edited by the researcher who conducted the interviews within 48 hours.

We triangulated information (Yin, 2018) from these interviews with archival data provided by the interviewees and identified by the researchers, including safety cases published by AV companies that detail their operations, job postings for frontline roles at AV firms, and news articles that mention frontline labor roles for different robotaxi services. These sources confirmed the existence of equivalent roles across multiple robotaxi firms. We used the information from these different sources to generate a list of frontline labor roles for robotaxi operations for use our cost model.

Table 2: Summary of data sources used to identify labor roles in robotaxi services.

<table>
<tr><td rowspan="9">Interviews</td><td>Category</td><td>Position</td><td>Number of Unique Interviewees</td><td>Total Length of Interview(s) (min)</td></tr>
<tr><td rowspan="3">Commercial Operations</td><td>Frontline Worker</td><td>6</td><td>280*</td></tr>
<tr><td>Mid-level Manager</td><td>5</td><td>166</td></tr>
<tr><td>Senior Manager</td><td>5</td><td>209</td></tr>
<tr><td rowspan="2">Pilot Program or Government-Run Deployment</td><td>Operations Manager</td><td>3</td><td>182**</td></tr>
<tr><td>Policy/Communication Manager</td><td>2</td><td>278</td></tr>
<tr><td rowspan="2">External Perspective</td><td>AV Operations Expert</td><td>3</td><td>131</td></tr>
<tr><td>AV Regulations Expert</td><td>3</td><td>357</td></tr>
<tr><td colspan="2">Total:</td><td>27</td><td>1603</td></tr>
<tr><td rowspan="5">Observations</td><td colspan="2">Observation Type</td><td>Number of Observations</td><td>Total Duration (min)</td></tr>
<tr><td colspan="2">Robotaxi rides</td><td>13</td><td>237</td></tr>
<tr><td colspan="2">Observations of robotaxi command center</td><td>1</td><td>360</td></tr>
<tr><td colspan="2">Observations of robotaxi fleet maintenance depot</td><td>1</td><td>120</td></tr>
<tr><td colspan="2">Total:</td><td>15</td><td>717</td></tr>
<tr><td rowspan="7">Archival Documents</td><td colspan="2">Document Type</td><td>Number of Items</td><td>Total Number of Pages</td></tr>
<tr><td colspan="2">News Articles Mentioning Frontline Robotaxi Roles</td><td>7</td><td>64</td></tr>
<tr><td colspan="2">AV Firm Public Reports and Petitions</td><td>5</td><td>168</td></tr>
<tr><td colspan="2">Job Postings for Frontline Robotaxi Roles</td><td>20</td><td>39</td></tr>
<tr><td colspan="2">Reports about AV Regulations</td><td>4</td><td>271</td></tr>
<tr><td colspan="2">Supplementary Responses and Documents from Interviewees</td><td>4</td><td>17</td></tr>
<tr><td colspan="2">Total:</td><td>40</td><td>559</td></tr>
</table>

*One 30min interview included a Frontline Worker and a Mid-Level Manager. Interview length counted here.
**One 64min interview included an Operations Manager and a Policy/Communication Manager. Interview length counted here.

3.2 Frontline Labor Roles in Robotaxi Services

Although vehicle automation may eliminate drivers, AV firms still require human labor for numerous other roles, many of which are new labor roles that do not exist in non-AV taxi services. These roles include not only cleaners and safety oversight monitors (or “remote monitors”) included in prior studies, but also field support agents, customer service agents, and coordinators. **Table 3** compares how traditional and robotaxi services use a combination of technology and human labor to fulfill necessary functions of a taxi-type service, including brief descriptions of each of these functions. Field support agents provide in-person response in case of incidents ranging from minor problems that inhibit the vehicle’s progress (e.g., a flat tire), to more severe issues like a collision. These workers also assist with general vehicle service tasks like vehicle cleaning and refueling. Customer service agents answer rider questions, issue safety reminders, and manage rider behavior. Coordinators facilitate the sharing of information both within and beyond the AV firm. Their primary responsibilities include managing communication with key stakeholders in case of incidents, collecting and reporting data in support of mandatory reporting requirements, and facilitating collaboration across different teams (see [paper name removed to protect anonymity during review] for more detailed descriptions of the aforementioned roles and their responsibilities).

Some AV firms also include an in-vehicle attendant as an additional layer of support or to comply with existing regulations requiring a safety driver. We exclude this role from our model as most robotaxi firms have either already removed or plan to eliminate this role in the future. We bound our analysis to the steady-state operations of robotaxi services and exclude labor involved in training the AV systems.

Table 3: Comparing labor and technology roles in traditional and robotaxi services.

Function	Function description	Taxi Service	Robotaxi Service
Vehicle general service	Vehicle cleaning, refueling, start-up procedures ("Pre-flight checks")	Driver	Field Support Agent
In-vehicle passenger support	Assisting ADA riders, providing entertainment, managing conflict between riders	Driver	In-Vehicle Attendant or Vehicle Design
Customer service	Answering questions about the service, managing rider behavior	Driver & Dispatcher	Customer Service Agent
Driving	Operation of the vehicle	Driver	Automated Driving System
Incident response	Assisting riders, speaking with Emergency Management Services (e.g., in case of accident)	Driver	Field Support Agent + Coordinator
Fare collection	Collecting payment for ride	Driver/App	App
Dispatch	Matching vehicle to riders, allocating vehicles in service area	Dispatcher (+ Computerized dispatch technology)	Dispatch algorithm
Vehicle maintenance	Repairs to vehicle (and sensors), oil changes, tire rotations	Mechanic	
Remote monitoring	Providing remote assistance to the vehicle as needed	N/A	Remote Monitor
Information Processing	Coordinating communication between roles, documenting processes, collecting information for mandatory reporting	N/A	Coordinator

3.3 Cost Model

We develop cost models to compare the fare per mile values of traditional taxi and robotaxi services. We base our cost models on Nunes and Hernandez's (2020) framework, but separate out labor as its own cost category and include financing of the automation technology (i.e., sensors and computing equipment) as a separate expense for the robotaxi calculation (**Equation 1**). We summarize each component of the cost models below and provide detailed descriptions of each individual input calculation in the Appendix. For robotaxis, we compute fare per mile values for a baseline scenario as well as four alternative scenarios described in the Scenario Analysis section below.

$$\textit{Fare per mile} = \frac{\textit{Vehicle Financing} + \textit{Technology Financing} + \textit{Licensing} + \textit{Insurance} + \textit{Maintenance} + \textit{Cleaning} + \textit{Fuel} + \textit{Profit} + \textit{Labor} + \textit{G\&A}}{\textit{Capacity Utilization Rate}} \quad \textbf{(1)}$$

Prior cost model studies assumed annual mileage values ranging from 36,000 to 100,000 miles per year (Bösch et al., 2018; Compostella et al., 2020; Fagnant and Kockelman, 2016; Greenblatt and Saxena, 2015; Nunes and Hernandez, 2020; Sperling et al., 2018). We assume an annual mileage of 65,000 miles per year for our baseline taxi and robotaxi models based on the average annual mileage for a taxi in New York City (Schaller Consulting, 2006) and test additional annual mileage values in the robotaxi scenarios.

Capacity Utilization Rate is defined in this study as the number of passenger miles traveled divided by the total miles traveled (passenger miles + unoccupied miles). Cramer and Krueger (2016) calculated taxi and UberX utilization rates for five U.S. cities and found utilization rates between 32.0-54.9%. We assume a utilization rate of 50% in our baseline models in alignment with Nunes and Hernandez's (2020) utilization rate of 52% for their San Francisco-based model and explore alternative utilization rates in the robotaxi scenarios.

Vehicle Financing covers costs associated with the fixed expense of the vehicle. Following prior studies, our baseline models assume no down payment, an annual fixed interest rate of 7%, a 3-year loan payment period, and a 5-year vehicle lifespan (Compostella et al., 2020; Nunes and Hernandez, 2020). We use the mean price for a hybrid electric vehicle (as developed in Compostella et al. (2020)'s ground-up cost model) and test potential cost savings from purpose-built AVs in one of the robotaxi scenarios.

Technology Financing provides an estimate for automation capital costs, including sensors, computing equipment, and data storage expenditures. We assume the same interest rate, loan payment period, and technology lifespan as for the vehicle financing calculation. In a 2021 interview, the CEO of the robotaxi firm Waymo asserted that their vehicles cost approximately the same as a moderately equipped Mercedes S-Class (in the mid-$100,000 range) (Moreno, 2021). Public reporting also estimated the cost of Cruise's autonomous Chevrolet Bolt between $150,000 to $200,000 (Mickle et al., 2023). Eight of our interviewees offered estimated costs of over $100,000 per AV, with five interviewees estimating a cost of over $250,000 per AV (the remaining interviewees did not provide estimates). Deducting the cost of the base vehicle, these estimates suggest that automation costs could still exceed $100,000. We assume a technology cost of $150,000, which we exclude from the traditional taxi model.

Licensing accounts for fees levied on for-hire vehicles. Future robotaxi services could fall under either existing taxi regulatory structures or those for TNCs. We test both a taxi and TNC licensing fee structure and find that our model is not highly sensitive to either. We use Chicago's taxi fee structure for our baseline models (BACP, 2020). In some cities, licensing occurs through a medallion system which can impose an additional high cost on taxi operators. We explore the effects of a medallion system in one of the scenarios.

Insurance covers the monthly cost to insure the vehicles. A monthly insurance premium of $682 is assumed in our baseline scenario based on the average monthly taxi insurance rates for fleets of greater than 100 vehicles (Bodine and Walker, 2023). Prior studies have proposed that vehicle automation will alter maintenance, fuel, and insurance costs. We exclude these effects in our baseline robotaxi scenario due to their uncertain nature but include some in our robotaxi scenarios.

Maintenance covers routine vehicle maintenance and repair. Two studies evaluating the operational expenses of TNC drivers in Seattle and New York find that maintenance expenses average approximately 5 to 7 cents per mile (Parrott and Reich, 2018; Reich and Parrott, 2020). Usage of vehicles for taxi and ride-hailing purposes is presumed to be equivalent, and a value of 6 cents per mile is assumed for the baseline models.

Cleaning accounts for the cost of interior and exterior vehicle cleaning. We assume that taxi drivers clean the interiors of their vehicles every other day using $6 do-it-yourself cleaning supplies and clean the exterior of their vehicles using a $10 automatic car wash once per week (Rainstorm Car Wash, 2023). Given the sensitive nature of their sensors, robotaxi vehicles must be cleaned by hand by field support agents. We account for the robotaxi cleaning costs as part of the field support agent labor cost, assuming that the cost of the worker is greater than the marginal cost of the cleaning supplies required to perform the cleaning task.

Fuel estimates the gasoline costs for operating robotaxi services. We use current estimated gas prices (AAA, 2023) and fuel efficiencies for hybrid vehicles (EPA, 2021).

Profit accounts for the firm's profit margin. We assume that robotaxi firms will aim to achieve at least the same profit margin as current taxi firms and adopt Nunes and Hernandez's (2020) assumption of $0.27/mile.

Labor covers the cost of frontline workers for and robotaxi services. For taxi services, we include costs for taxi drivers and dispatchers. We assume wages of $15.82/hour for drivers and $17.05/hour for dispatchers based on the mean hourly wages for those roles in the U.S. Taxi and Limousine Service industry (Bureau of Labor Statistics, 2023a, 2023b). We assume that for 24/7 operations a taxi firm would require two driver shifts and three dispatcher shifts. Each dispatcher would be responsible for 20 vehicles (Nunes and Hernandez, 2020).

We include the following labor roles for robotaxi services: remote monitors, field support agents, customer service agents, and coordinators. For 24/7 operations, we assume three eight-hour shifts for each role. We use recent job postings by AV companies on contractor websites and on general job sites such as Indeed for equivalent positions to set hourly wages for the roles: $19/hour for customer service agents and remote monitors, $24/hour for field support agents, and $29/hour for coordinators (Adecco, 2023; Cruise, 2023b; ICONMA, 2023; Indeed, 2023). We assume an overhead rate of 1.59 that applies to one full-time worker per shift (Nunes and Hernandez, 2020).

A 2023 statement from the robotaxi firm Cruise's CEO described how the firm's remote monitors typically manage between 15-20 vehicles each (Kolodny, 2023). We assume a 1:16 worker to vehicle ratio for both the remote monitors and the customer service agents in the *AV Baseline* model. As described in **Table 3**, field support agents are responsible for cleaning and preparing the robotaxi vehicles prior to their use. One field support agent can prepare a vehicle in approximately 20 minutes (Interview with Field Support Agent, 2023), meaning 24 vehicles could be prepared per 8-hour shift if one worker is always preparing a vehicle. In addition to preparing vehicles, field support agents must also be stationed in the deployment area in order to quickly respond to incidents. We assume a 1:6 ratio for field support agents to vehicles to account for their responsibilities both within the vehicle depot and out in the field. Coordinators are a more specialized role that help manage communication between the other labor roles. We assume a 1:5

ratio between the coordinators and the remote monitors, which translates to a 1:80 coordinator to vehicle ratio.

General and Administration (G&A) accounts for additional administrative costs. We assume that the traditional and robotaxi firms are similarly structured centralized firms and have similar G&A costs. We adopt Nunes and Hernandez's (2020) assumption of $0.05/mile.

3.4 Monte Carlo Simulation

Prior studies have accounted for variation in service usage by considering multiple spatial and temporal utilization scenarios and location-specific input values (Becker et al., 2020; Bösch et al., 2018). For each scenario, we conduct a Monte Carlo simulation to account for variation and uncertainty in a broader number of model inputs. In the Monte Carlo simulations, inputs are modeled as distributions rather than single values. For each distribution, we take 10,000 random draws and then compute the fare per mile for each draw, resulting in 10,000 estimates representing a *distribution* of the fare per mile rather than a single estimate. This process allows us to pass through uncertainty about the model inputs into the estimated fare per mile, which we then use to compute summary statistics such as the mean fare per mile. For the miles per trip input as well as one mileage-based licensing fee, we assume log-normal distributions to match the distributions of public datasets on taxi operations from the City of Chicago (City of Chicago, 2023) and the City of New York (New York City Taxi & Limousine Commission, 2023a). For all other inputs, we assume normal distributions with mean values equal to our assumed baseline scenario values and standard deviations selected based on a combination of real-world data and assumptions such that the resulting distributions fell within defined boundaries (see the Appendix for specific assumptions for each input).

3.5 Scenario Analysis

Cost per mile values for robotaxi services will depend on a number of operational factors that will vary by location and by time (e.g. future technological conditions). To account for these possibilities, we explore four alternative scenarios to our baseline robotaxi scenario and compare the fare per mile value for each: *AV Advanced Technology*, *AV High Usage*, *AV Medallion System*, and *AV Lower Density Region*. **Table 4** details the changes to specific model inputs for each scenario.

***AV Advanced Technology*:** This scenario captures operational improvements that may occur as the performance of the AV technology improves. Stephens et al. (2016) propose a 40%-80% reduction in insurance premiums for fully-automated vehicles due to lower potential accident rates. Fagnant and Kockelman (2016) assume reduced maintenance requirements for AVs due to smoother operation. Greenblatt and Saxena (2015) posit fuel savings of 80% due to more efficient fuel usage. For this scenario, we assume insurance reductions of 50%, fuel reductions of 20%, and maintenance reductions of 10%. We also assume that technology improvements reduce the demands on different workers, allowing robotaxi operators to increase the number of vehicles handled by each worker. Finally, we assume that the price of the AV technology decreases to the $10,000 value used in prior studies.

***AV High Usage*:** AVs are predicted to induce greater travel demand by opening up new mobility options for individuals (Appleyard and Riggs, 2017; Milakis and van Wee, 2020; Wadud et al., 2016; Williams et al., 2020). Higher utilization might also occur via greater sharing of rides which would reduce the number of unoccupied vehicle miles. Multiple AV companies are exploring business models that involve dual-use of their fleets for both passenger and goods delivery services which could further increase vehicle utilization and annual mileage (Cruise, 2023c; Perez, 2018). In this scenario, we increase annual mileage to 80,000 miles/year and the capacity utilization rate to 70%. We assume that higher vehicle use would increase maintenance costs by 20% due to greater wear on the vehicles and would also shorten the lifespans of the vehicle and the AV technology to 4 years.

AV Medallion System: Some U.S. cities such as New York and San Francisco regulate the number of taxis in operation by issuing a limited number of permits, typically called medallions. Over time, the value of these medallions in some cities has risen significantly. In 2019, the median price of a medallion in New York was approximately $225,000 (New York City Taxi & Limousine Commission, 2023b). Given their high price, medallions are often financed in a similar manner as a vehicle. As described in the *Licensing* section above, the regulatory scheme for robotaxis is not yet determined. Mo et al. (2021) propose limiting the number of licenses available for robotaxis to avoid overcrowding of the transportation network with these vehicles. In this scenario, we explore the impact of a medallion-based regulatory structure for robotaxi services, adopting the medallion financing scheme assumed by Nunes and Hernandez (2020).

***AV Lower Density City*:** Private AV companies will only deploy commercial services in regions in which they can achieve profitability. This scenario investigates the economics of robotaxi deployment in a lower density city. We assume that in a lower density city, more individuals will own personal vehicles and that demand for robotaxi services will be lower, decreasing both the annual mileage and the capacity utilization rate. We assume an annual mileage of 64,000 and a utilization rate of 43.6%, approximate values for taxi-type services in Seattle (Cramer and Krueger, 2016; UITP, 2020). The population density of Seattle is approximately 8,791.8 people/mi^2 compared to Chicago's density of 12,059.8 people/mi^2 (US Census Bureau, 2020). Moreover, we assume that decreased usage will reduce the wear on the AV, increasing the vehicle and AV technology lifespans to 6 years.

Table 4: Changes to input values for each scenario.

Scenario	Scenario Description	Scenario Value (change to means only)
Advanced AV Technology	Maintenance	Reduced by 10%
	Insurance	Reduced by 50%
	Fuel	Reduced by 20%
	Remote Monitor	Worker-to-vehicle ratio increased to 1:30
	Customer Support	Worker-to-vehicle ratio increased to 1:30
	Field Support	Worker-to-vehicle ratio increased to 1:8
	Coordinator	Worker-to-vehicle ratio increased to 1:150
	AV Tech Price	Decreased to $10,000
High Usage	Annual Mileage	Increased to 80,000 mi/year
	Maintenance	Increased by 20%
	Capacity Utilization Rate	Increased to 70%
	Vehicle Lifespan	Decreased to 4 years
	AV Tech Lifespan	Decreased to 4 years
Medallion System	Medallion price	$225,000
	Down payment percent	20%
	Percent of down payment paid upfront	25%
	Financing period for down payment	7 years
	Financing period for remaining medallion cost	5 years
	Medallion interest rate	5.4%
	Medallion lifespan	20 years
Lower Density Region	Annual Mileage	Decreased to 64,000 mi/year
	Vehicle Lifespan	Increased to 6 years
	AV Tech Lifespan	Increased to 6 years
	Capacity Utilization Rate	Decreased to 43.6%

4 Results

4.1 Cost by Category and Fare per Mile Estimates

Our simulation results reveal that while all AV robotaxi scenarios can achieve lower per-mile costs than non-AV taxi services, labor still remains a key operational cost for robotaxi services (**Figure 1**). **Table 5** presents the mean total cost, the mean cost by category, and the mean fare per mile estimates from the Monte Carlo simulations (i.e., out of the 10,000 simulations run, in which input values were randomly drawn from assumed distributions, the presented values are the means of the simulation outputs). For example, Monte Carlo simulations produced 10,000 values for the total labor cost for each scenario. **Table 5** presents the mean estimated labor cost for each scenario.

The labor costs alone for the AV scenarios already exceed the total cost per mile estimates from most prior studies ($0.76-$1.04 /mile for this study, see **Table 1** for estimates from prior studies). Technology advancements that allow for fewer workers to manage a greater number of vehicles could, however, significantly reduce labor expenditures and allow for the low (<$1.50/mile) total operational costs predicted by prior studies (**Table 5**, *AV Advanced Tech* scenario). The *AV Medallion System* scenario has the highest operational cost per mile amongst the AV scenarios due to the added expense of the medallion, highlighting regulatory decisions that could impact the economic competitiveness of AV services.

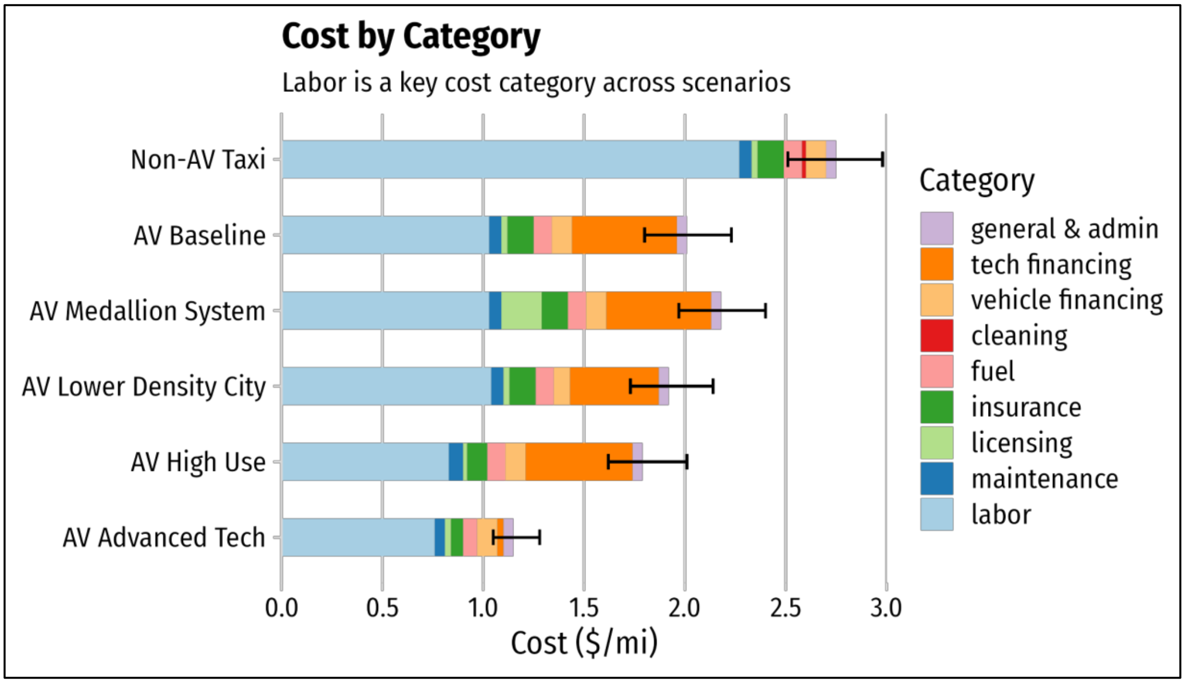

Figure 1: Operating costs by category for each scenario with 95% quantile bars from the Monte Carlo simulations of the total cost across all categories.

Even with the additional labor roles, the labor costs for the AV scenarios remain significantly lower than those of the non-AV taxi service. Even with the added technology expense and substantial labor cost, the mean cost for the *AV Baseline* scenario is $1.99/mi compared to $2.74/mi for the *Non-AV Taxi* scenario. Assuming similar utilization rates and profit margins for all scenarios, these lower costs translate to lower fares (**Figure 2**). The mean estimated fare per mile for the *Non-AV Taxi* scenario is $6.03/mile compared to $4.52/mile for the *AV Baseline* scenario (**Table 5**), suggesting that robotaxi providers could out-compete human-driven taxi services on price. Though the *AV Medallion System* scenario is the highest cost AV scenario, the lower utilization rate in the *Lower Density City* scenario results in a higher fare per mile value. We discuss the importance of utilization rates in the following section.

To evaluate our findings in light of current taxi operations, we compare our estimated fare per mile values to existing fare data from two public datasets on taxi operations from the City of Chicago (City of Chicago, 2023) and the City of New York (New York City Taxi & Limousine Commission, 2023a). We use data from the year 2019 to capture market conditions prior to the COVID-19 pandemic but during a period when taxis faced competition with established Transportation Network Company (TNC) services such as Uber and Lyft. We find that our mean non-AV taxi fare is similar to those of Chicago and New York City, suggesting that our model is fairly reflective of current operational practice (Chicago: $5.70/mi, New York: $5.69/mi).

Table 5: Mean total cost and mean cost by category estimates from the Monte Carlo simulations.

	Non-AV Taxi	AV Baseline	AV Medallion System	AV Lower Density City	AV High Use	AV Advanced Tech
Cost ($/mi)						
Labor	2.27	1.02	1.02	1.04	0.83	0.76
Cleaning	0.02	0.00	0.00	0.00	0.00	0.00
Fuel	0.09	0.09	0.09	0.09	0.09	0.07
General & Admin	0.05	0.05	0.05	0.05	0.05	0.05
Insurance	0.13	0.13	0.13	0.13	0.10	0.06
Licensing	0.03	0.03	0.20	0.03	0.02	0.03
Maintenance	0.06	0.06	0.06	0.06	0.07	0.05
Tech Financing	0.00	0.52	0.52	0.44	0.53	0.03
Vehicle Financing	0.10	0.10	0.10	0.08	0.10	0.10
Total Cost ($/mi)						
Mean:	2.74	1.99	2.16	1.91	1.79	1.15
Std. Dev:	0.14	0.13	0.14	0.13	0.12	0.07
Fare ($/mi)						
Mean:	6.03	4.52	4.87	5.01	2.95	2.84
Std. Dev:	0.31	0.28	0.29	0.31	0.18	0.15

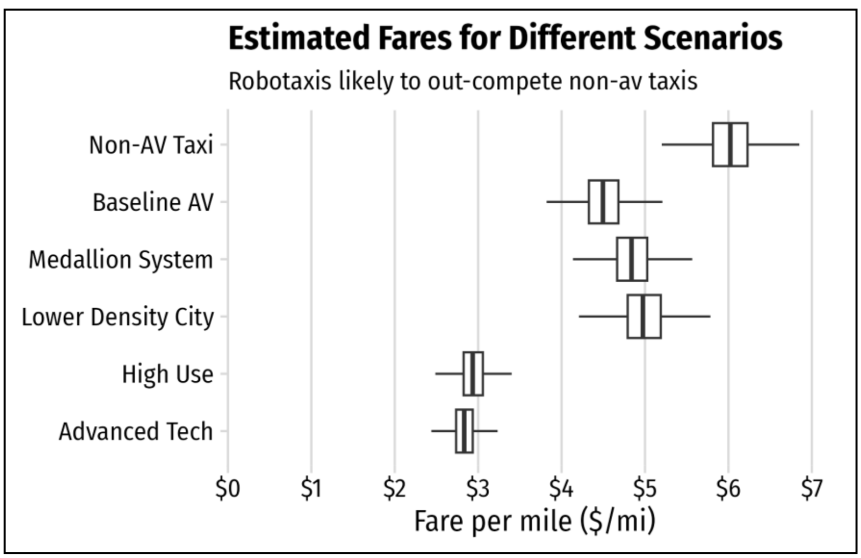

Figure 2: Distribution of per-vehicle fare per mile estimates for each scenario from Monte Carlo simulations.

4.2 Investigating Sensitive Inputs

We perform two systematic sensitivity checks, one on the taxi-specific model inputs and one on the AV-specific model inputs, testing values 50% higher and 50% lower than the assumed values in the baseline scenario. We exclude model input values for which changes to the assumed value would not make logical sense (e.g., time conversion variables, number of days per year). We find that both models are most sensitive to capacity utilization rate and annual mileage (**Figure 3**).

This sensitivity suggests that operational features may play a larger role than labor in determining the cost of future robotaxi services.

The *AV Baseline* model is also sensitive to the price and lifespan of the AV technology. Given that the technology price is expected to decrease over time, the *AV Baseline* results may be interpreted as a conservative estimate for how traditional taxis and robotaxis might compete with one another. The *AV Advanced Technology* scenario offers a more bullish picture of a future in which technology prices decline significantly. AV firms will still need to develop vehicle designs that can maintain or increase their vehicles' lifespans and the lifespans of their AV technology suites to remain competitive. While not as influential as utilization-related inputs, both models are also sensitive to the wages and labor ratios for their associated labor roles.

4.3 How Sensitive Inputs Impact Fare per Mile Values

To further investigate the most sensitive inputs, we compute how fares vary based on changes to the three most sensitive model inputs: *capacity utilization rate*, *annual vehicle miles traveled*, and *labor ratios*. **Figure 4** shows these results for the *Non-AV Taxi*, *AV Baseline*, and *AV Advanced Technology* scenarios, with the bands reflecting 95% quantile outputs from the Monte Carlo simulation results. The curves show how the fare changes with changes to each input, holding all other inputs constant. We select these three scenarios to capture status quo non-AV taxi operations, current robotaxi operations, and an optimistic scenario for future robotaxi services where the technology improves to achieve greater performance at lower cost. The points on each curve denote the assumed value used for each scenario.

The exponentially decreasing nature of these input parameters emphasizes the importance of robotaxi firms' ability to achieve utilization rates equivalent to or higher than those of existing taxi services. If their usage falls relative to that of non-AV taxi services, they could lose their competitive edge in terms of lower fare per mile rates. Operational and technology advancements characteristic of the *AV Advanced Technology* scenario would give robotaxi firms greater leeway with such operational pressures and could allow them to expand into regions that have historically had lower taxi utilization.

As **Figure 4** demonstrates, fare per mile is also highly sensitive to lower labor ratios (i.e., fewer vehicles per worker), but firms reach economies of scale relatively quickly. This sensitivity explains the notable difference in labor costs between the non-AV and robotaxi services shown in **Figure 1**. Though robotaxi firms may employ a greater number of types of frontline workers, robotaxi workers can handle more vehicles per worker. Taxi firms can, and presumably do, optimize their dispatcher-to-vehicle ratios but are limited by their need to always have a driver operating each vehicle. In contrast, robotaxi firms can have remote monitors and customer service agents manage greater numbers of vehicles at a time.

At a labor ratio of approximately three vehicles per worker (e.g., per remote monitor), the mean fare per mile for the *AV Baseline* scenario reaches approximately $6, the estimated mean value for the *Non-AV Taxi* scenario. One interviewee with experience in the airline industry noted that flight dispatchers—a role which the interviewee described as more equivalent to the remote monitor position than an air traffic controller—typically work at around a 1:5 worker-to-aircraft ratio (Interview with Senior-level Manager, 2023). A 1:5 ratio would raise the mean estimated fare per mile value to over $5 for the *AV Baseline* model, which is still lower than that of a non-AV taxi service. While we did not use this ratio in our baseline scenario, we note that regulation that limits how many vehicles each worker can monitor could result in higher costs for robotaxi firms and limit their competitiveness against existing services.

Striving for the lowest possible number of workers, however, may not be necessary either. After an initial steep decline, fare per mile values are relatively similar for labor ratios of 1:15 or higher. Some prior studies have assumed ratios of one remote monitor for 80 vehicles (Negro et al., 2021). Striving for such a high number of vehicles per monitor might impose cognitive overload challenges for the monitor (Mutzenich et al., 2021) while offering fairly marginal cost reductions. AV firms will have to weigh these marginal cost reductions against impacts to service quality for their passengers and performance consequences for their workers (e.g., mental workload, situational awareness).

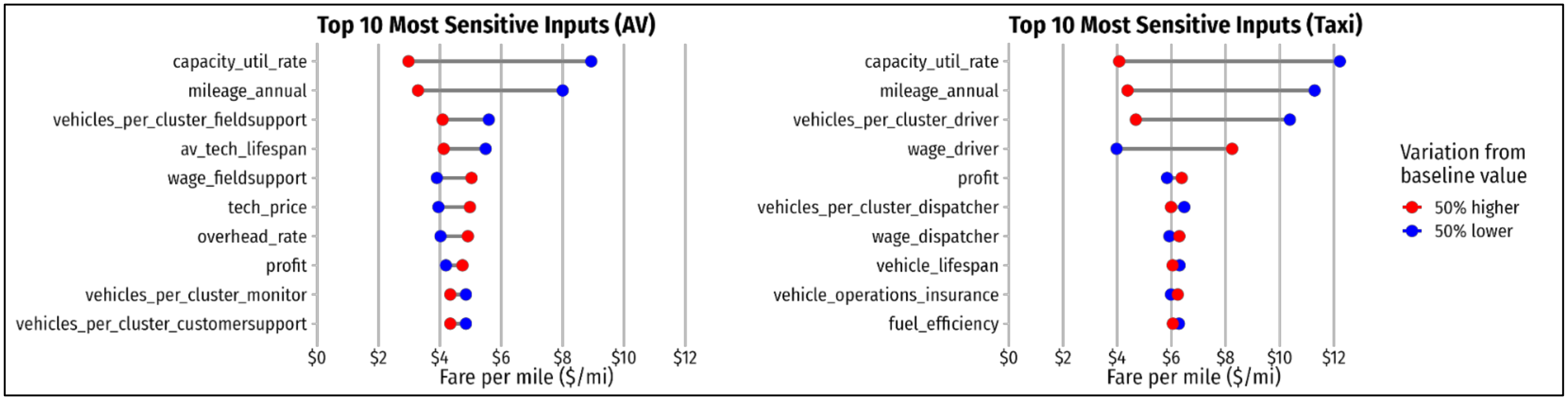

Figure 3: Top ten most sensitive model inputs for the *AV Baseline* and *Non-AV Taxi* models. Input values were varied 50% higher and 50% lower than the assumed values

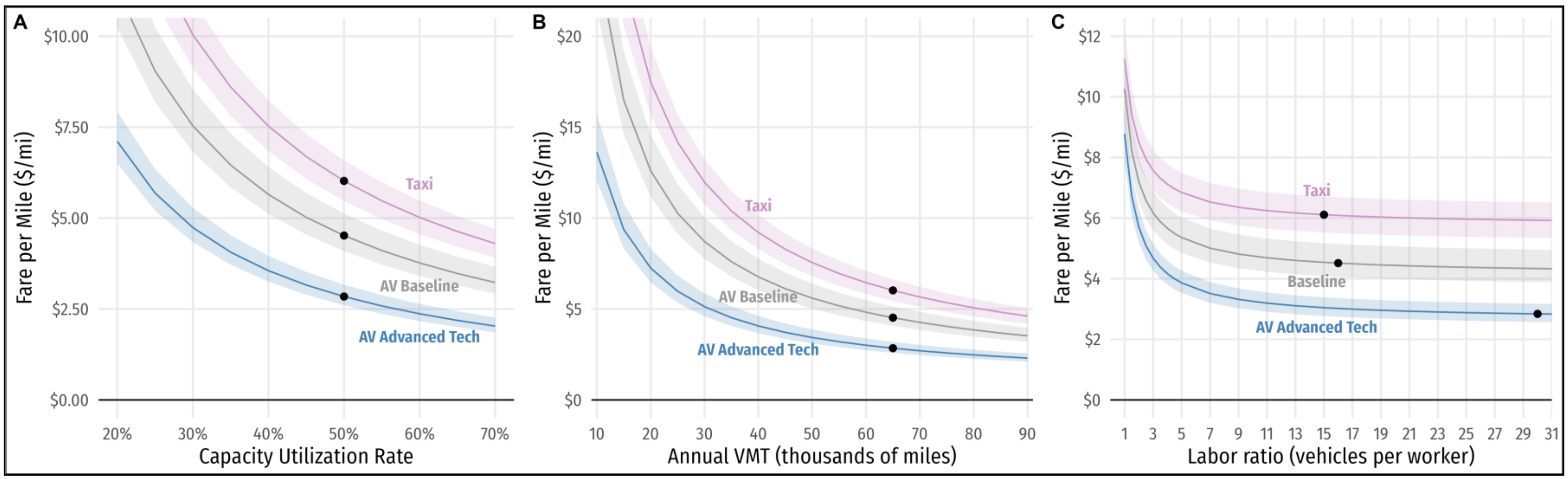

Figure 4: Estimated mean fare per mile values across a range of A) capacity utilization rates, B) annual vehicle miles traveled values, and C) labor ratios for the *Non-AV Taxi, AV Baseline*, and *AV Advanced Technology* scenarios. Colored bands indicate 95% quantile bands from the Monte Carlo simulations. Black points mark the assumed value used for the scenarios.

4.4 Wage Outcomes

We now turn to an examination of the differences in wages between frontline workers in the taxi and robotaxi systems. Based on the roles examined in this study, we find that wages would shift higher for frontline workers in an AV service (**Figure 5**), but the total number of workers would decrease by approximately 57% for the *AV Baseline* scenario (from 216 to 93 workers to service a 100-vehicle fleet). In the *AV Advanced Technology* scenario, the total number of workers decreases by approximately 76% due to increases in the number of vehicles managed by the labor roles, but the distribution of the wages remains similar to that of the *AV Baseline* scenario. For the AV scenarios, wages follow a bimodal distribution, with the limited number of coordinator roles earning higher wages than the field support, customer service, and remote monitor roles, which make up most of the labor force. We emphasize that these distributions do not capture other labor roles and job numbers that may be created to support AV services for the development and production of AVs, their distribution, and roles involved in a potentially expanded upgrades and repairs industry (Chamber of Progress, 2024).

The wage distributions are the same for the *AV Baseline* and *AV Advanced Technology* scenarios as we assume that in the future, the wages for the frontline roles will remain the same but that labor ratios will decrease (see Table 4 for details). Ultimately, robotaxi firms could change how much they pay their frontline workers, either increasing or decreasing wages based on, among other factors, the perceived difficulty of the roles and the available supply of workers. Such changes would alter the wage distributions for frontline workers.

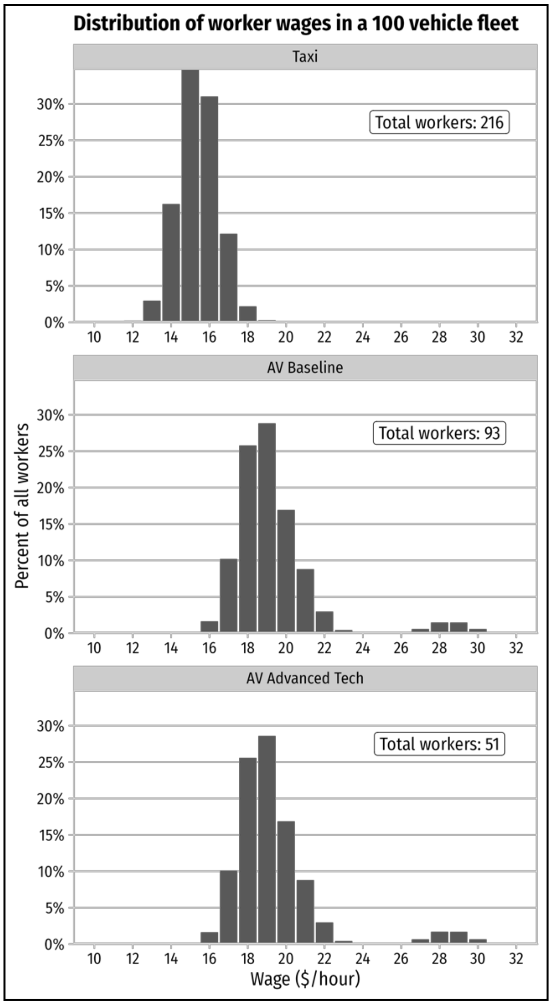

Figure 5: Estimated percent of workers that would fall within a given wage range for the *Non-AV Taxi*, *AV Baseline*, and *AV Advanced Technology* scenarios. Plotted values depict the mean values from the Monte Carlo simulations (i.e., mean value for estimated total workers and mean values for estimated percent of workers within each wage bin).

5 Discussion

In this study, we provide the first model and analysis of robotaxi services with labor assumptions that are grounded in currently deployed robotaxi services in the U.S. Our estimated labor cost of **$1.02/mi** is higher than nearly every prior estimate: **$0.01-0.19/mi** (depending on the country) (Becker et al., 2020), **$0.21/mi** (Bösch et al., 2018), **$0.22-0.23/mi** (depending on utilization) (Negro et al., 2021), and **$0.34/mi** (Wadud, 2017; Wadud and Mattioli, 2021). Only Nunes and Hernandez (2020) suggest the potential for a higher labor cost than our estimate, offering an estimate ranging from **$0.10-$2.40/mi** for cleaning and safety oversight services. The high end of their estimate range assumes a remote monitor to vehicle ratio of 1:5, which would significantly drive up the labor cost (a finding mirrored in our sensitivity analysis); however, using our *AV Baseline* assumption of 1:16 for the remote monitor to vehicle ratio, their labor cost estimate drops to approximately **$0.15/mi**, aligning with the low estimates from prior studies. Our inclusion of additional labor roles, surfaced through our data collection efforts, reveals that robotaxi labor costs are substantially higher than previously expected.

Even after accounting for higher labor expenditures and for technology costs that are more representative of the current state of technology, our results still align with prior findings that robotaxi services could out-compete traditional taxi services on price, and that utilization rates and annual mileage remain the most influential factors affecting robotaxi competitiveness (Negro et al., 2021; Nunes and Hernandez, 2020). If regulation or technological requirements impose limitations on the number of vehicles workers can manage, however, labor costs could increase and limit robotaxi competitiveness.

Beyond supporting conclusions about robotaxi competitiveness, the granularity in robotaxi labor roles included in this study extends knowledge in two important ways. First, greater granularity allows researchers and practitioners to better understand the bounds for reducing labor costs based on critical technological and operational considerations. There are practical limits to how quickly a human can clean delicate sensors or how quickly a worker can travel to respond to an accident. For remote monitors, these limitations include challenges with maintaining situational awareness (Mutzenich et al., 2021). Service providers must consider labor ratios and labor costs not only to achieve target costs, but also to achieve target levels of quality and safety of their services. By cataloguing the many different labor roles involved in robotaxi services, this study enables researchers and practitioners to critically examine these operational considerations for different roles and how they might impact service quality and safety. Researchers may also use these additional considerations to refine future simulation studies of AV services.

Significant interest exists in how AV services will impact jobs, including the number of job losses and their geographic distribution, and the nature of emerging roles (Leonard et al., 2020). Our model's sensitivity to utilization suggests that robotaxi services may remain limited to regions like dense urban areas that offer sufficiently high demand, potentially bounding where labor displacement for taxi and ride-hailing drivers might occur. We note that the populations of dense, urban regions are also predicted to have more positive perceptions of AVs and higher predicted AV adoption rates (Bansal et al., 2016; Krueger et al., 2016).

While we do not attempt to offer economy-level predictions about the numbers of jobs lost or gained due to vehicle automation[1], we do provide an early estimate for how robotaxis might impact labor forces on a more localized, sector-based scale based on the labor ratios and utilization rates for which robotaxi firms may strive. We find that these impacts could range from a potential 57 to 76% reduction in the number of frontline workers. However, the distribution of wages in jobs supporting robotaxi services is shifted higher than that of jobs supporting traditional taxi services. We emphasize that automation often reshapes labor in unexpected ways (NASEM, 2017) and that other jobs may also emerge to support robotaxi services in the future.

We acknowledge a number of limitations in this study. As with prior studies, we base many of our assumptions on data for existing taxi services due to the limited scale of existing robotaxi deployments. Vehicle automation could impact operational costs in unexpected ways not captured by our scenarios. Moreover, we do not yet know how public preferences for autonomous services might unfold and impact demand (see Gkartzonikas and Gkritza (2019) for a review of stated preference and choice studies on this topic) and whether robotaxi firms could realistically achieve the capacity utilization rates and mileage values assumed in the *AV Baseline* scenario.

In this study, we are focused on a U.S. context in which labor costs are relatively high. Becker et al. (2020) find that the cost-saving effects of automation are stronger in higher-income locations than in lower-income locations where labor costs may not be reduced as significantly by

[1] See Beede et al., (2017), Groshen et al. (2018), and Chamber of Progress (2024) for U.S. estimates or Alonso Raposo et al. (2019) for European Union estimates.

automation. Thus, the results of this study regarding robotaxi competitiveness, job losses, and wage changes would generalize to other higher-income contexts, but may not hold for lower-income locations.

We consider a specific set of labor roles that does not capture additional jobs that may be involved in the technology training, development, production, and distribution of AVs. Altering the system boundary of analysis could change the results in terms of the number of jobs required to support robotaxi services, their associated wages, and potentially the geographic location of those jobs (as occurred with prior forms of automation and offshoring of labor (Goos et al., 2014)). Additional roles such as an in-vehicle attendant may also be critical for early adoption of robotaxi services and for providing critical in-person support to specific rider populations for whom the service would otherwise be inaccessible (Kaplan and Helveston, 2023; Kyriakidis et al., 2020).

Shared rides could not only offer greater profitability for robotaxi firms but also promote more sustainable transportation systems. Though not explicitly included in our model, shared rides would allow for higher per-trip fares without raising the trip price for individual riders and could increase capacity utilization for individual vehicles. Shared rides could also confer additional benefits to robotaxi operators including meeting demand with a smaller fleet size and reduced vehicle miles traveled, and handling surges in demand more effectively (Hyland and Mahmassani, 2020). As with existing taxi-type services, however, interest in shared rides is limited, with most riders preferring not to share rides (Kang et al., 2021; Kaplan and Helveston, 2023; Krueger et al., 2016). We base our model on hybrid vehicles but acknowledge the value of a combined electric and autonomous future. Switching to fully-electric fleets could reduce some operational costs (i.e., lower fuel cost) but at the expense of higher up-front prices, which would increase the vehicle financing costs (Fulton et al., 2017). Furthermore, AV computational requirements have been shown to reduce electric ranges by 10-15% (Mohan et al., 2020), which could limit their feasibility to achieve higher utilization rates and / or annual mileage.

There may be other costs that we have omitted; Litman (2023), for example, notes that vehicle automation would also add additional annual software, mapping, and subscription costs. We do not explicitly model costs these as we consider them part of the AV technology costs. Finally, this study assumes labor ratios based on current practice for robotaxi services that still operate in limited operational design domains. Further research within the domain of human factors engineering could provide better estimates for AV service labor ratios that are safe and economically efficient. Future research could also add additional scenarios that explore how different labor ratios might alter the wages for various frontline work positions and subsequent wage distributions and consider the different costs associated with use of an electric vehicle fleet. This study's *AV Advanced Technology* scenario captured a future in which technology costs decline significantly. Future work should track the rate at which costs actually decline, and whether additional technology costs are later introduced.

Finally, this study largely adopted the perspective of a private commercial fleet operator. Local governments are also exploring, and in some cities already implementing, AV robotaxi and roboshuttle (fixed-route) services to supplement or fulfill the role of their public transit systems. Public operators may be less concerned with profitability and may be interested in, or required to consider, other indirect or intangible costs like public health and transportation equity (see Labi et al. 2023 for a review of many of these additional cost factors). Transportation planners and researchers interested in incorporating such costs could modify our model to weigh investments in AV services against other types of non-automated services.

6 Conclusion

As robotaxis expand into an increasing number of cities, transportation planners and researchers need to consider the full operating costs of AV services and how they might realistically substitute or complement existing services. This competition will not only determine how AVs might impact the safety, environmental sustainability, and accessibility of transportation systems but also how they might impact transportation jobs. This study refines prior AV cost models by detailing frontline labor roles involved in existing robotaxi services and incorporating technology estimates more reflective of current prices. We find that, after accounting for additional labor roles, labor costs for robotaxis are far higher than previously estimated. Despite these higher costs, robotaxis can still out-compete taxis on price, and utilization rates and annual mileage will ultimately serve as the limiting factors for robotaxi competitiveness. If jobs shift from taxi to robotaxi services, the number of jobs could decrease by between 57 to 76%, though the distribution of wages would shift higher. Significant uncertainty remains regarding how robotaxi services will impact our transportation networks and the labor systems that support them. We hope that these results can help to inform dialogue between planners, policymakers, workers, and members of the public about how emerging technologies not only could—but should—interact with our transportation systems.

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Model Inputs

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