Predicting Rail Transit Impacts with Endogenous Worker Choice: Evidence from O'ahu*

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Abstract

Expanding public transportation can improve the accessibility of work opportunities. However, predicting the labor market effects of new transit infrastructure is difficult due to endogenous worker decisions. I examine a large public transit rail project on the island of O'ahu, Hawai'i. Using block-level commuter flow and travel-time estimates, I propose and estimate a novel quantitative spatial model of location and mode choice for low and high-income workers. I estimate that the new rail system increases public transit mode share and the employment rate, but does not reduce the average commute duration. Crucially, accounting for endogenous worker decisions is essential for accurately estimating these effects.

Keywords: Transportation; Transit; Residential Choice; Quantitative Spatial Model; Spatial Mismatch
JEL classification: J20; J60; R13; R23; R40; R58

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1 Introduction

Constructing public transit infrastructure can improve labor market opportunities by reducing commuting costs. However, estimating the commuter benefits of new transit infrastructure is challenging because of endogenous worker responses and land market effects. I attempt to account for endogenous worker behavior by constructing a novel Quantitative Spatial Model (QSM) using detailed, block level, commuter flow and travel time information. I apply the model to estimate the labor market effects of a new rail transit line on the island of O'ahu, Hawai'i.

The first segment of O'ahu's rail system began operating in 2023. The proposed benefits of building rail on O'ahu included (1) a reduction in commute duration for workers, (2) an increase in public transit mode share, and (3) an improvement in labor market outcomes through improved worker access to jobs. I propose and estimate a model that tests for these benefits, accounting for endogenous worker decisions. I find evidence of the rail system achieving goals (2) and (3) but not (1).

The general equilibrium effects of rail are unknown without accounting for endogenous worker decisions. I collect detailed, block-level commute time data and block-level bilateral commuter flow data. Through a QSM, I estimate worker preferences across commuting routes and modes, for both low and high-income workers. I then apply these parameters to estimate the general equilibrium effects of the new rail infrastructure on commute times, public transit mode share, and employment. Under static worker choice, I find that rail produces commute time savings for the average worker. After accounting for endogenous decisions, I find that the rail system leads to a small *increase* in the average commuting time on O'ahu, as workers substitute away from cars and towards transit, and substitute towards longer routes. Despite failing to reduce average commute time in spatial equilibrium, I find the rail system leads to an increase in public transit mode share and in the aggregate employment rate.

The theory that spatial isolation from jobs may induce joblessness was proposed as the spatial mismatch hypothesis in Kain (1968). Andersson et al. (2018) provided recent empirical work that confirmed the continued importance of spatial mismatch in the US. Some papers have relied on natural experiments in which transit access changed exogenously to identify causal labor market effects (Holzer et al., 2003; Tyndall, 2017), these studies found a positive impact of transit access on employment.

Longitudinal data on individual workers is not typically available to researchers analyzing the effects of transportation systems. As a result, accounting for endogenous household location decisions typically relies on directly modeling the choices of workers. QSMs have been implemented to estimate aggregate and distributional benefits of new urban amenities, particularly transportation systems. The basis for spatial urban models comes from the monocentric city model (Alonso, 1964; Muth, 1969; Mills, 1967), and the polycentric city model (Fujita and Ogawa, 1982). Workers accept higher commuting time to access areas with lower housing costs. In a spatial equilibrium, these costs and benefits must lead to an equalization of utility over space. The extension of the basic urban model to incorporate structural modeling approaches, based on the discrete choice methods of McFadden (1973), was developed in Anas (1981) and Epple and Sieg (1999) and further extended in several papers including Bayer et al. (2004), Sieg et al. (2004), Bayer et al. (2007), Bayer and McMillan (2012), Ahlfeldt et al. (2015), and Behrens and Murata (2021).

This paper relates most closely to a recent literature on estimating benefits of transit infrastructure using structural neighborhood choice modeling. Severen (2019) examined the impact of rail transit on the labor market in Los Angeles. Tyndall (2021) analyzed light rail transit (LRT) systems across four US cities, and Chernoff and Craig (2022) examined distributional effects of a rail expansion in Vancouver. Each of these papers implemented a neighborhood choice model to understand the interaction between housing markets, labor markets and endogenous worker decisions in estimating the effects of transit infrastructure. I incorporate features of these models.

I describe and apply a new model to a data set with more spatial detail than has been used in past literature. I incorporate block-level bilateral matrices for both commuter flows and a block-level data set of travel times from an online wayfinding service. As discussed in Dingel and Tintelnot (2023), urban discrete choice models using granular data can suffer from estimation bias if the observed commute matrix is "sparse," meaning there are few observed commuters relative to the size of the commute matrix being estimated. I provide some innovations on this topic by proposing a new, nested estimation strategy. I reduce matrix sparseness by pooling multiple years of data and collapsing flow information from the census block to the census tract level. However, given the availability of block-level information, I then reconcile worker location distributions to specific blocks within tracts by nesting a housing market and labor market within tracts. This is the first paper to make use of block-level information in an urban discrete choice model, while directly addressing the issue of matrix sparseness.

A specific focus of this paper is to predict the role of long-run endogenous sorting on the impacts of new rail infrastructure. By executing a model across several stages of a rail phase-in period, I estimate the relative role of direct commuting cost reductions and the role of endogenous household location, mode, and labor market decisions. I recover estimates of rail's impact on average commuting time, transit mode share, and the island-wide employment rate. I find that accounting only for direct commuting cost savings fails to capture the aggregate impact of transit. Workers with strong preferences for using transit are likely to sort toward stations (Glaeser et al., 2008), while workers with a preference for driving will sort away from stations, repelled by rising land costs. Low-income workers are more likely to use transit but are also sensitive to rent increases, meaning the effect of a local public transit amenity that raises neighborhood demand might attract or repel low-income workers, depending on the magnitude of the two effects (Tyndall, 2021). The QSM approach attempts to account for these competing effects and estimate the total island-wide impacts of rail.

The paper will proceed as follows. Section 2 describes the empirical setting. Section 3 provides a discussion of data. Section 4 describes the structural estimation methodology. Section 5 outlines the model solution method. Section 6 provides results and Section 7 concludes.

2 Rail Transit on O'ahu

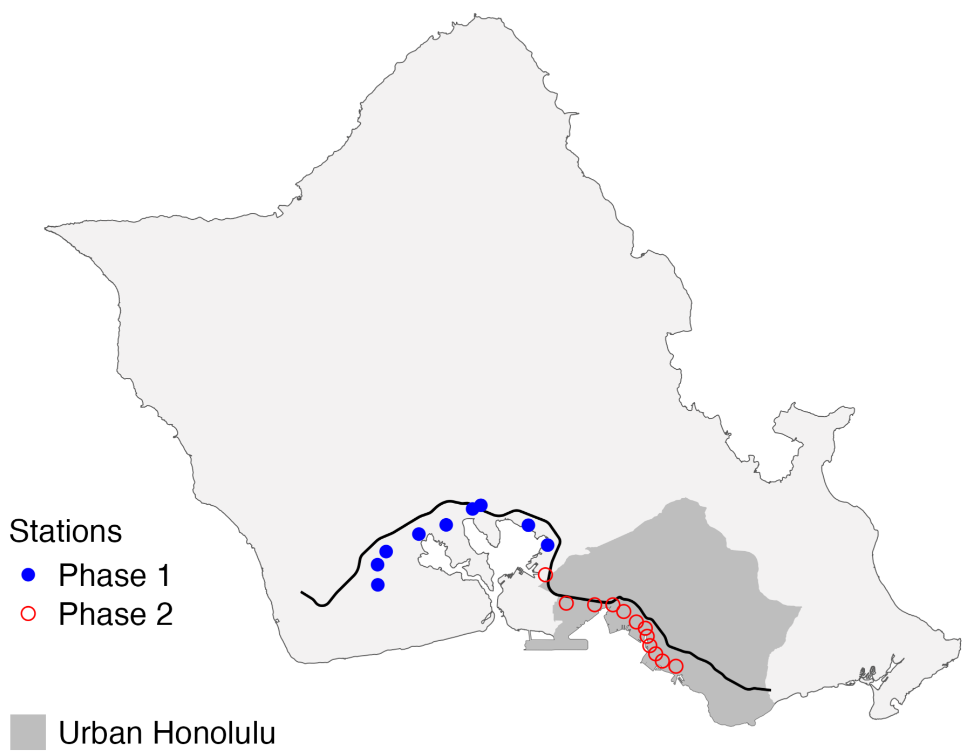
I study O'ahu's first public transit rail line. The system has a so-called "hybrid-rail" design, combining features of both light and heavy rail systems. The system is elevated, with track and station platforms supported on concrete pillars. The full line is planned to include 21 stations, which span 31 km. The western edge of the system extends to the Kapolei neighborhood, and the easternmost station is located at Ala Moana, a major mixed-use area in the urban core of Honolulu.[1] The opening of the full 21-station line is set to be completed in stages, with the westernmost 9 stations opening in 2023, the next 4 stations opening in 2025, the next 6 stations opening by 2031, and the 2 easternmost stations opening at an unconfirmed later date. I will refer to the initial nine stations as Phase 1 and the remainder of the stations as Phase 2. I provide analysis on the effects of Phase 1 as well as the full line.

Figure 1 shows the locations of the rail stations on the island of O'ahu. The path of the rail line roughly follows the H1 Interstate Highway. The H1 serves commuters from

[1]The precise location of the easternmost stations are the topic of debate and could be revised. Currently, construction has begun to Ka'ākaukukui Civic Center, with the two easternmost stations still in the planning phase.

the west side of the island who commute into the urban core of Honolulu. East-bound traffic on the H1 is severe during rush hour, which served as a motivation for providing a high-capacity public transit option on this route. Household incomes on the west side of O'ahu are generally lower than on the east side of O'ahu, meaning the proposed rail route is aligned to provide access to the downtown job center for working-class populations.

Figure 1: Location of Rail Stations on O'ahu and the H1 Highway



The H1 Interstate Highway is shown in as a black line. Phase 1 stations opened in 2023. The 10 westernmost Phase 2 stations are scheduled to open by 2031, with the final two stations opening at a later date.

The history of passenger rail planning on O'ahu spans several decades. City documents discussing the prospect of an urban rail line can be found dating back to the 1960s. In 2005, funding was secured to begin construction of the project, and in 2011 construction began. The rail project has experienced significant delays in construction and large cost overruns. Even after construction began, there was significant political uncertainty regarding whether the project would be completed. For example, Honolulu mayoral campaigns from 2004 to 2020 centered on whether to complete or abandon construction of the rail line. Political opposition to the construction of rail often centered on concerns with cost overruns. When construction began, capital costs were expected to be $4 billion, with $1.6 billion coming from the Federal Transit Administration (FTA). Projected costs rose steadily over the following years. The current projected cost of the line is $12.4 billion. Even considering the high costs of transportation infrastructure throughout the US (Brooks and Liscow, 2022; Gupta et al., 2022), the O'ahu system construction costs are extremely high relative to comparable cities, in terms of either total cost or costs per system-mile.

Prior to the opening of the rail line, the rail corridor was served by significant rush-hour bus service. O'ahu provides relatively extensive bus service compared to similar sized US cities. However, buses travel within general traffic in almost all cases, meaning they are subject to traffic delays and accompanying trip duration uncertainty.

The island of O'ahu is coterminous with the City and County of Honolulu.[2] O'ahu provides an excellent study location for several reasons. First, as a small island, the relevant local labor market is cleanly defined. Typically, studies of urban labor markets impose assumptions to define a study area, often adopting Census boundaries. In the case of O'ahu, the boundaries of the study area are clear and there are no border-area spillover effects to be considered. Access to O'ahu from the neighboring Hawaiian Islands is only possible by air travel. O'ahu is small enough that commuting is possible across the entire island, though large enough to be comparable in size to the commuting sheds of other US metropolitan areas. Second, the O'ahu rail system represents a significant infrastructure investment and the first rail connection on the island. The lack of existing rail infrastructure makes the treatment definitions clearer, as I do not need to consider network effects for a preexisting rail system.

O'ahu shares many urban form characteristics with midsized American cities, such as significant highway infrastructure and primarily single-family zoned land use, surrounding a relatively dense urban core. Demographics on O'ahu are unique in several dimensions. Median household income on O'ahu ($87,700) is higher than the median household income across US metropolitan areas ($69,600), while the college education rate is similar. O'ahu has a high Asian population share (43%) and a high share of Native Hawaiians and Pacific Islanders (10%) when compared to other metros in the

[2]Counties in Hawai'i do not contain distinct municipalities; rather, they operate under a combined city-county system.

US. The prerail rate of public transit commuting on O'ahu (7.2%) is about 40% higher than the average rate across other metros. Demographic information for the study area is provided in Table 1, with comparisons to average US metro conditions and the US as a whole.

Table 1: Demographic Characteristics of Study Area

	O'ahu	**US Metros**	**USA**
Population	979,682	284,298,061	331,449,281
Median household income ($)	87,722	69,591	64,994
College education rate† (%)	35.7	34.7	32.9
Labor force participation (%)	66.4	64.3	63.4
Unemployment (%)	2.6	3.5	3.4
Median age	38.2	38.0	38.2
Owner-occupancy rate (%)	57.5	63.0	64.4
White (%)	20.2	68.2	70.4
Black (%)	2.5	13.4	12.6
Asian (%)	42.6	6.3	5.6
Native Hawaiian or Pacific Islander (%)	10.0	0.2	0.2
Hispanic (%)	10.0	20.6	18.2
Average commute time (minutes)	28.0	27.5	27.0
Commuter mode share:			
Drove alone (%)	78.6	83.2	83.8
Public transportation (%)	7.2	5.2	4.8
Walking (%)	5.6	2.5	2.6

Data are from the 2020 five-year American Community Survey.
† Bachelor's degree or above, among population 25 years and older.

3 Data

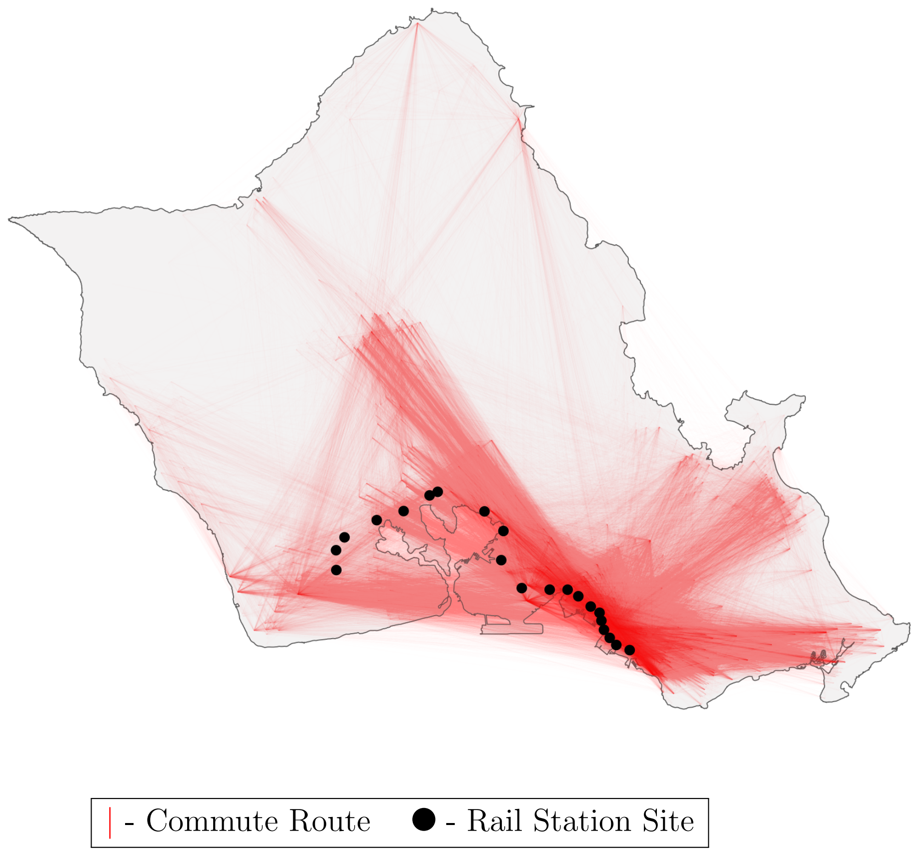
I construct a route level data set, with granularity at the census block level. I rely on block-level bilateral commuting flow data from the 2014–2021 Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) and a block-level commuting time matrix provided through the transportation routing firm Travel Time. Blocks are defined according to 2010 US Census boundaries.

LODES breaks out commuter flows by worker income. I categorize workers into two worker types, low- and high-income workers, relying on the cut-off values used in LODES. Low-income workers are defined as those earning less than $40,000 annually, and high-income workers as those earning more than this amount.[3] Across the 2014–

[3]Using the $40,000 threshold is a limitation of the LODES data. I refer to "low" and "high"

2021 LODES, I observe 1,908,183 unique block-to-block commutes. Low-income workers cover 1,308,668 unique routes, while high-income workers cover 1,055,170 unique routes. The routes include 12,136 unique home locations and 8,276 unique work locations. I collapse the eight years of data to create a cross-sectional matrix, in which the number of commuters using a route is the average across the 2014–2021 period. Figure 2 visualizes the block-to-block flows. Notably, a large share of O'ahu's workers commute within the corridor that will be served by rail.

Figure 2: Block-to-block Commuter Flows



Each line connects a worker's home and work location. Darker lines indicate that more workers share that commute route.

I gather extensive trip level data from the transportation routing firm Travel Time. For any pair of latitude and longitude coordinates, the Travel Time Application Pro-

income workers for simplicity, but "high-income" workers might be more accurately considered as mid-to-high-income workers.

gramming Interface (API) returned an estimate of the commuting time. I queried the API for every block-to-block route on O'ahu. The API incorporates predicted traffic and transit schedule conditions for a selected time. I set parameters to collect data for the quickest possible route that would allow a worker to get to their destination by 9:00 am on a Wednesday in order to match likely commuting time. I use the geographic centroid of each census block as the origin and destination point, and calculate driving and transit times for all block-to-block pairs.

I first collected a full matrix of commute times in October 2021, prior to the opening of the first segment of the rail line. In August 2023, I again collected a full travel time matrix, which reflected conditions that included the first segment of the rail system. Having both pre- and post-treatment commute time matrices allows for the calculation of travel time savings brought on by the rail line.

To my knowledge, this is the most granular data set of commuting time matrices that has been used in the related literature. Pedestrian access to transit stations is an important determinant of transit use. Using blocks rather than tracts better captures spatial access to transit nodes, which can be obscured when using tract centroids. As one example, the easternmost station in the system, "East Kapolei," is located 7.2 km from the geographical centroid of it's surrounding census tract, and 3.7 km from the population-weighted center of that census tract. Both of these distances are too far to walk in a reasonable commute. Therefore, a census tract based model would be poorly suited to reconcile observed commutes. Using census blocks overcomes this issue, as there are many blocks within walking distance of the station.

Table 2 provides average travel times for driving and public transit across all one-way commutes. Across all block-to-block pairs, the average driving time is 23 minutes, with an average distance of 18.5 km. When weighting routes by the number of workers who actually complete that commute according to LODES data, the average worker-weighted driving time is 19.5 minutes, and the average distance is 15.0 km. The average public transit commute time for block-to-block routes where transit is available is 62.6 minutes, or 54.7 minutes when weighted by the number of commuters. The average commuting times calculated with Travel Time data are comparable to estimates from the American Community Survey (ACS) reported for O'ahu. After the first phase of rail is completed, and ignoring endogenous worker behaviors, I estimate the average public transit commute time across all workers falls by 1.3 minutes.

Figure 3 shows the relationship between driving times and public transit times for the data covering the period before the rail system was running. For nearly every route,

Table 2: Summary Statistics, Average Route Level Data

	Travel Time (mins)	Travel Distance (km)
All Observed Routes		
Driving	23.0	18.5
Transit, pre-rail	62.6	-
Transit, post-Phase 1 rail	61.0	-
Transit, post-Phase 2 rail†	57.9	-
Weighted by Workers		
Driving	19.5	15.0
Transit, pre-rail	54.7	-
Transit, post-Phase 1 rail	53.4	-
Transit, post-Phase 2 rail†	50.7	-

Average route characteristics among observed commutes on O'ahu. Public transit figures ignore routes that cannot be completed by transit or would take more than two hours one-way.
† Phase 2 transit times are approximated using the the method described in this section.

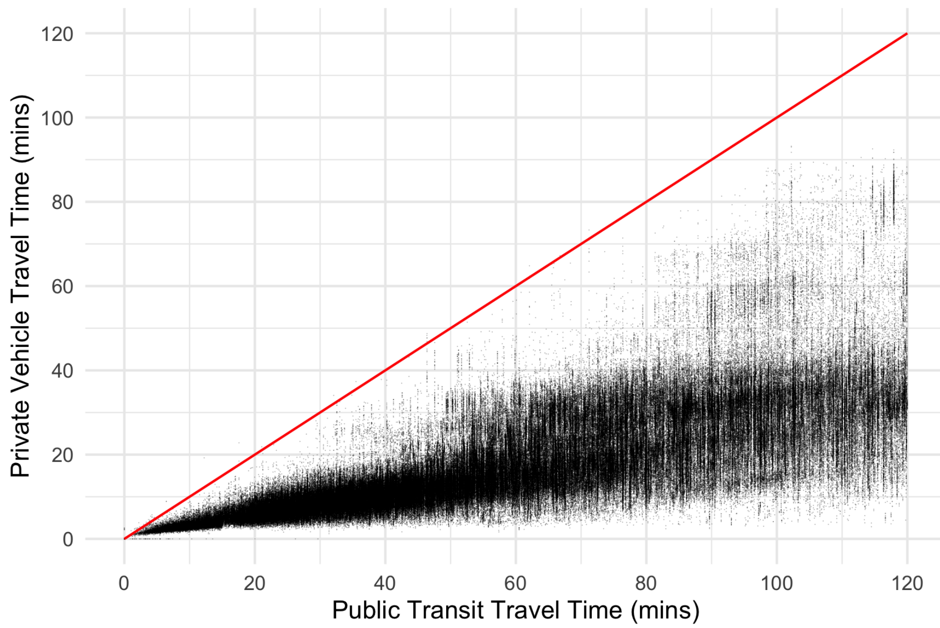
driving provides a shorter trip time than public transit. For 96.3% of routes, public transit takes more than twice as long as driving; for 74.7% of routes, transit takes more than three times as long, and for 48.8% of routes, transit takes more than four times as long.

Figure 4 provides examples of the trip time data, showing the area that can be covered by driving and public transit for an example origin location. The left images show the area that can be covered within 30 minutes, while the right images show the area that can be covered in one hour. Comparing the top and bottom panels, the area accessible by driving in a given time is drastically larger than the area that can be accessed by public transit. Almost the entire island is accessible in a one-hour drive, while only a small fraction is accessible through a one-hour public transit commute. The figures reflect prerail commute times.

I restrict the data set by dropping any commute that is estimated to take more than two hours one-way, as these are unlikely to be viable daily commutes. This restriction applies only to public transit commuting as there are no two census blocks on O'ahu that are more than two hours apart by driving.

Figure 5 displays the change in the average public transit commute time from every block with a worker population. Panel A shows the reduction in public transit commute time generated by the opening of the first phase of the rail system. I calculate the difference in commuting times between the two rounds of travel time data collection.

Figure 3: Drive Times vs. Public Transit Times for Observed Commute Routes, before Rail

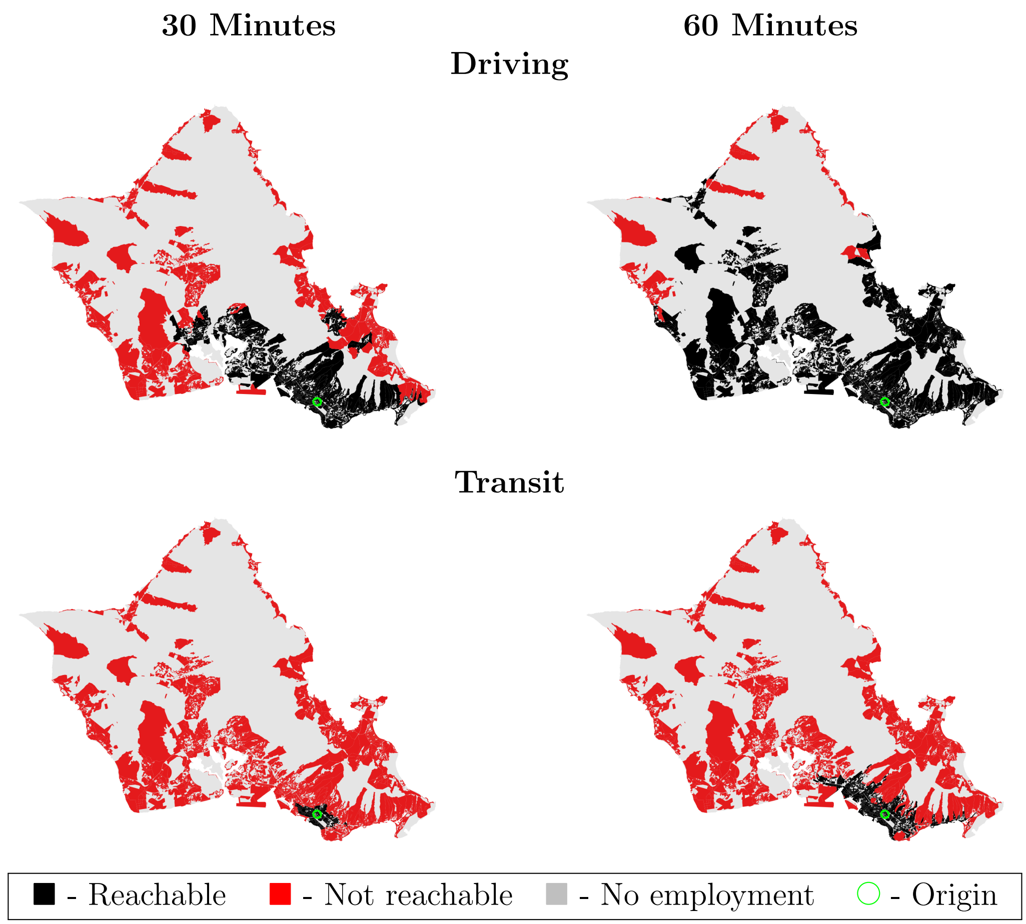


Each point represents one commuting route. The red line would indicate trips where private vehicle and transit commute times are equal. The figure displays all routes that can be completed in under two hours by both driving and public transit (569,339 observations).

The result gives me precise time savings brought on by the implementation of the first phase of rail service. Because the second phase is not yet operating, I do not have access to a full matrix of travel times under the scenario of full rail service. I approximate the time savings produced by Phase 2 by first calculating the average reduction in public transit commuting time experienced by any route where the straight line connection between origin and destination bisects the Phase 1 rail corridor, where the corridor is defined as the area within two kilometers of the rail line. I find the average route bisecting the Phase 1 corridor experienced a 6.0% reduction in public transit commuting time. I apply this measure to Phase 2, by reducing public transit commute times by 6.0% for any route that bisects the Phase 2 rail corridor. I will consider a scenario where the introduction of rail also impacts driving times along the rail corridor (Appendix A).

Between collecting pre- and post-rail commute time matrices, some bus routes were altered. Changes included the removal of some bus routes that serviced the same corridor as the rail system. Some other routes were altered for unrelated reasons as part

Figure 4: Job Locations Accessible from One Origin Location

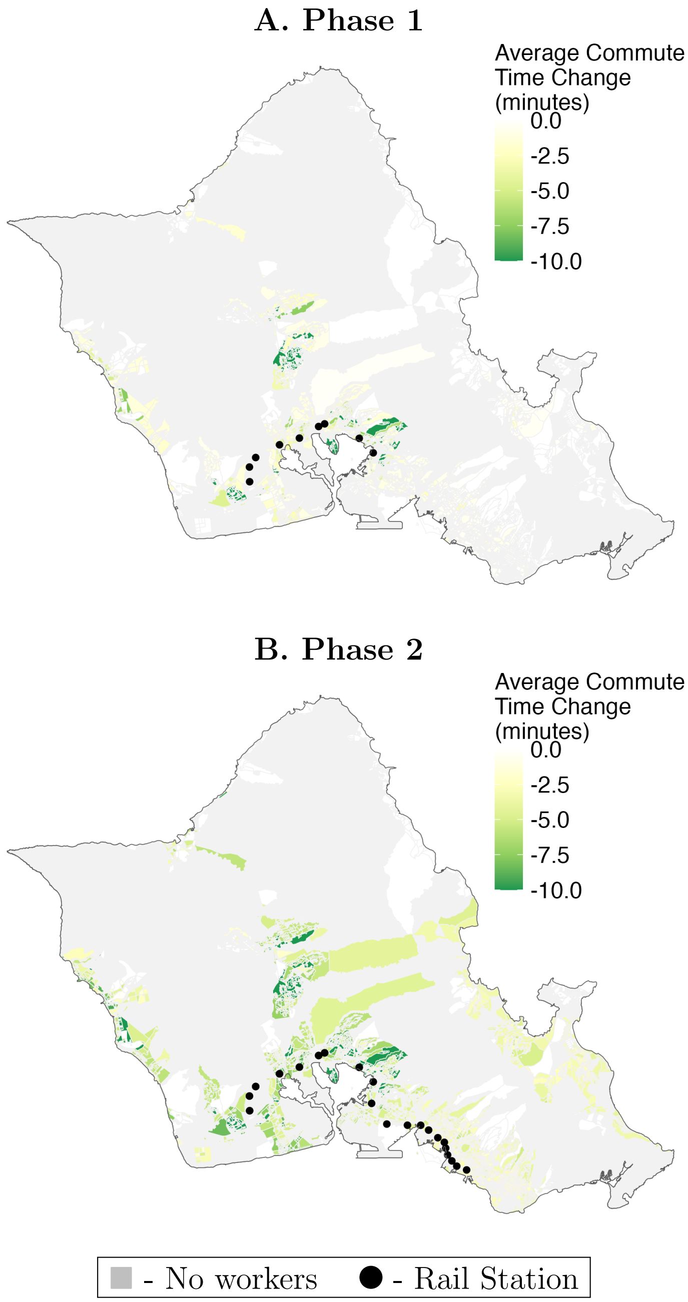


Block-level information is presented, showing which areas are reachable through driving and public transit from an origin location placed in Honolulu's city-center. I find that driving provides dramatically more job opportunities to a worker when compared to using public transit. The displayed data capture the prerail period.

of regular system optimization efforts by the local transit agency. To focus analysis on the impact of rail, I clean the data by assuming rail did not *increase* transit time for any pair of blocks. For every route, I assume the post-rail travel time is the minimum of the observed pre or post-rail time. I also assume that transit time reductions only occurred for routes that pass through the rail corridor, holding other routes constant to pre-rail estimates.

The model will incorporate estimates of local housing costs as a parameter. I approximate annualized local housing costs for each census tract in the model. I use deed transfer records from O'ahu. The data covers every real estate transaction from

Figure 5: Reductions in Average Public Transit Commuting Time Due to Rail



Phase 1 represents the effect of the opening of the westernmost nine stations, while Phase 2 represents the opening of the entire 21-station system. Estimates apply to the unweighted average commuting time difference across all block-to-block pairs for public transit routes.

2010–2021. I calculate the median sales price of a home at the census tract-level, assume an annual price-to-rent ratio of 20, and assign annual housing costs to each block based on which tract it is located in. I estimate costs at the tract level rather than block level to reduce noise in areas with few transactions. Estimated annual housing costs calculated in this way range from \$11,750 to \$137,397, with a median of \$34,975 (or \$2,915 per month).[4] Because the model encompasses both renters and owners, this method gives a more accurate approximation of spatial variation in housing costs as compared to survey data on rents.

The model introduced below will also incorporate basic sociodemographic information, such as the employment rate. For demographic information I use 2020 five-year ACS.

4 Methodology

I propose a QSM to predict the effects of the new rail system on (1) average commute duration, (2) public transit mode share, and (3) the aggregate employment rate. I allow workers to choose their home location, work location, commute mode (driving vs. transit), and labor market participation. The model is built on the assumptions of the classic urban model. Workers are utility maximizing and face a trade-off between housing costs and commuting costs. I introduce two types of workers: low and high-income. Solving the model will yield preference parameters over routes and modes and allow worker behavior to be estimated in counterfactual scenarios.

The introduction of rail reduces some commuting costs. By holding constant worker preference parameters and resolving the model under alternative transit counterfactuals, I am able to estimate the impact of rail on aggregate worker outcomes inclusive of endogenous worker decision making.

Equation 1 is a Cobb-Douglas style utility function that governs worker preferences.

$$U_{ijkm} = (C - c_{s(i)jkm})^{\gamma_{s(i)}} H^{(1-\gamma_{s(i)})} \chi_{s(i)J(j)K(k)} + \xi_{ijkm} \tag{1}$$

Workers derive utility from numeraire consumption (C) and generic units of housing (H). Nonmonetary commuting costs (c) reduce consumption. Each worker (i) chooses a home location (j), work location (k), and mode of transportation (m). Mode choice is limited to driving or public transportation. Walking is considered as a component of public transportation. The share of income a worker spends on housing is set by $1 - \gamma_{s(i)}$. Each worker is either a high ($s(i) = h$) or low ($s(i) = l$) income worker.

[4] 2021 five-year ACS data records median monthly housing costs for owner-occupiers on O'ahu to be \$2,800, closely matching the median calculated from the deed transfer records.

$\chi_{s(i)JK}$ is a route and worker-type specific preference parameter. I define the home census block as j, the home census tract as $J(j)$, the work census block as k, and the work census tract as $K(k)$. Beyond differences in commuting costs (which are accounted for directly), some routes may provide higher utility than others based on their unique characteristics, such as housing and job prospects or any other route specific characteristics. Given spatial differences in job types and housing quality, different worker types may have different common preferences. All workers of the same type share a common evaluation of χ_{JK}. Resolving $\chi_{s(i)JK}$ will help produce realistic substitution patterns in the counterfactuals as workers of specific types will preferentially substitute towards routes that provide higher utility to their type, on average. An extreme value distributed error term (ξ_{ijkm}) captures the worker specific idiosyncratic preferences over each available route-mode option.

Nonmonetary commuting costs ($c_{s(i)jkm}$) are defined in Equation 2. $\zeta_{s(i)m}$ is the mode-specific cost of commuting per hour as a share of a worker's wage. $\zeta_{s(i)m}$ is allowed to differ across worker types, as they may have different preferences across modes. $\omega_{s(i)k}$ denotes hourly wage and τ_{jkm} represents the hours spent in commute.

$$c_{s(i)jkm} = \zeta_{s(i)m}\omega_{s(i)k}\tau_{jkm} \tag{2}$$

Each worker operates under a budget constraint, represented by Equation 3. Worker income ($w_{s(i)k}$) is determined by the worker's type and their work location. Workers exhaust their income[5] ($w_{s(i)k}$) on housing costs (Hp_j), numeraire consumption (C), and monetary commuting costs (θ_{jkm}). Monetary commuting costs will be calculated according to the mode selected and, in the case of driving, the distance of the commute. Workers choose a utility maximizing quantity of housing and pay the market housing costs in their home location (p_j).

$$w_{s(i)k} = Hp_j + C + \theta_{jkm} \tag{3}$$

A worker choosing a null work location ($k = \emptyset$) represents being out of the labor force. When out of the labor force, a worker pays no commuting costs and receives a government allocated income (ι).

The utility function and budget constraint combine to produce an indirect utility function, shown in Equation 4.

[5]Annual income and hourly wage ($\omega_{s(i)k}$) are related by assuming an eight-hour work day and 260 working days in a year: $w_{s(i)k} = \omega_{s(i)k} \times 8 \times 260$.

$$V_{ijkm} = (w_{s(i)k} - c_{s(i)jkm} - \theta_{jkm}) {\gamma_{s(i)}}^{\gamma_{s(i)}} \frac{1-\gamma_{s(i)}}{p_j}^{1-\gamma_{s(i)}} \chi_{s(i)J(j)K(k)} + \xi_{ijkm}$$
$$V_{ijkm} \equiv v_{ijkm} + \xi_{ijkm} \tag{4}$$

The extreme value distributed idiosynncratic error term enables a multinomial logit probability function (Equation 5). The function determines the probability that a worker selects a specific home, work, mode triple (P_{ijkm}). Upper-bar notation indicates the maximum value in the set.

$$P_{ijkm} = \frac{e^{v_{ijkm}}}{\sum_1^{\bar{j}} \sum_1^{\bar{k}} \sum_1^{\overline{m}} e^{v_{ijkm}}} \tag{5}$$

I calculate the public transit mode share for high and low income workers by summing all of the choice probabilities in which m is public transit (Equation 6). I will refer to the true (observed) public transit mode shares as $M_{s(i)}$ and the model generated values as $\mathcal{M}_{s(i)}$.

$$\mathcal{M}_{s(i)} = \sum_1^{\bar{j}} \sum_1^{\bar{k}} P_{ijk(m=\text{transit})} \tag{6}$$

5 Solution Method

My approach differs from much of the prior literature in three ways. First, I have access to a census block-level matrix of commuting times, which allows for a more granular analysis than has been possible previously. Second, I have both pre- and post-treatment commute time matrices, allowing me to calculate realistic commute time changes attributable to rail. Third, to accommodate granular data without succumbing to the overfitting issues identified in Dingel and Tintelnot (2023), I propose a new method that accommodates block-level worker choices while matching tract-to-tract bilateral commuter flows.

I first solve the complete cross-sectional model using data from the pre-rail period. I make use of cross-sectional variation in worker commuting behavior to recover preference parameters governing commute time costs and a vector of route by worker type preference parameters. Assuming that worker utility is equalized across space and observing actual housing cost and commuting cost information allows for the recovery of route specific preference parameters that necessarily compensate for spatial differences in utility implied by housing costs and transportation costs. I then use these parameters to run four counterfactual scenarios, which capture conditions across various rail and worker sorting conditions.

To estimate the model, I impose several exogenous parameters, shown in Table 3. Annual income is set to $19,859 for low-income workers and $85,326 for high-income workers. I recover these estimates from ACS microdata.[6] I set the out of labor force income to be $10,000.

Table 3: Exogenous Model Parameters

Symbol	Value	Description
$w_{s(i)=l}$	19.859	Low-income worker income ($1,000)
$w_{s(i)=h}$	85.623	High-income worker income ($1,000)
ι	10.000	Out of labor force income ($1,000)
$\gamma_{s(i)=l}$	0.53	Share of income spent on non-housing consumption (low-income)
$\gamma_{s(i)=h}$	0.85	Share of income spent on non-housing consumption (high-income)
$M_{s(i)=l}$	0.180	Initial public transit mode share, low-income workers
$M_{s(i)=h}$	0.085	Initial public transit mode share, high-income workers
$\zeta_{m=\text{driving}}$	0.93	Commuting cost per unit time as share of wage, driving
$\theta_{jk(m=\text{transit})}$	0.96	Annual monetary cost of transit commuting ($1,000)
$\theta_{jk(m=\text{driving})}$	$0.0589\times \mathrm{d}_{jk}$	Annual monetary cost of private vehicle commuting ($1,000), d=distance in km

I impose these parameters on the model.

I assume an individual worker spends a constant fraction of income on housing $(1-\gamma)$. Using O'ahu specific census microdata from the 2020 five-year ACS, I calculate the share of household income spent on gross rent or mortgage payments for workers earning above and below the $40,000 income threshold that divides low and high-income workers. ACS data indicates low-income workers spend 47% of income on housing and high-income workers spend 15% of income on housing, on average.[7] I use these estimates to parameterize γ. To facilitate solving tract-level route flows, I initially set housing costs (p_j) exogenously and uniformly within tracts, according to the tract-level estimates from transaction data, as described in Section 3.

I impose an estimate of the time cost of driving as a share of the wage rate. I select the parameter estimated in Small et al. (2005), which examined commuting behavior

[6] I use individual wage earnings from the 2020 five-year ACS microdata for Honolulu County. I drop workers with earnings of zero or less and take the mean value for workers in each income category (low vs high). I find that the main results are not sensitive to moderate changes in income level assumptions.

[7] Davis and Ortalo-Magné (2011) discuss and estimate this parameter for the US, finding that the average worker spends 24% of their income on housing.

in Los Angeles, finding drivers faced a time cost of driving equal to 93% of their wage rate. The parameter for public transit commuting will be determined endogenously to match the observed public transit commuting rates ($M_{s(i)}$).

I constrain the model to produce the public transit mode share observed in aggregate data. I impose mode share restrictions that are specific to worker type. I identify $M_{s(i)}$ directly from ACS data as 18.0% for low-income workers and 8.5% for high-income workers. I consider walking to be a component of public transit to avoid introducing an additional mode choice. Notably, public transit mode share among the low-income group is more than twice that of the high-income group. When solving the model, the worker type specific time costs of public transit use ($\zeta_{s(i)m=\text{transit}}$) are determined endogenously and allow the model to generate the correct public transit mode shares in the pre-rail scenario.

I impose monetary commuting costs (θ_{jkv}). For public transit users, I assume workers pay for 12 monthly transit passes each year, which cost \$960 in Honolulu ($\theta_{jk(v=\text{transit})} = 0.960$). For those driving, I approximate monetary commute costs using data from the American Automobile Association (AAA) (American Automobile Association, 2021). Assuming 260 working days in a year, AAA estimates of marginal commuting costs for a "medium sedan" imply \$58.87 in annual costs for every km of daily commuting. For each route I use the driving distance estimated in the Travel Time data. To arrive at route specific monetary costs, I multiply the two-way commute distance by the per km cost of driving.[8] I assume workers ignore the fixed costs of car ownership when choosing a commuting mode, as the decision to own a car reflects general mobility demand beyond commuting.

Workers implicitly make a labor force participation decision, as selecting a null work location ($k = \emptyset$) represents not working. When calculating the worker shares for $k = \emptyset$ "routes," I use ACS data on the number of working age residents in each census tract who are out of the labor force, and spread these workers uniformly across the tract's constituent blocks, as weighted by block population. I then scale up the number of workers out of the labor force to precisely match the island-wide labor force participation rate as recorded in the ACS data (66.4%). I assume worker non-participation is equally likely across worker types.

The model is solved simultaneously but has a nested structure as illustrated in Figure 6. Bilateral commuter flow counts for each worker type are matched for every

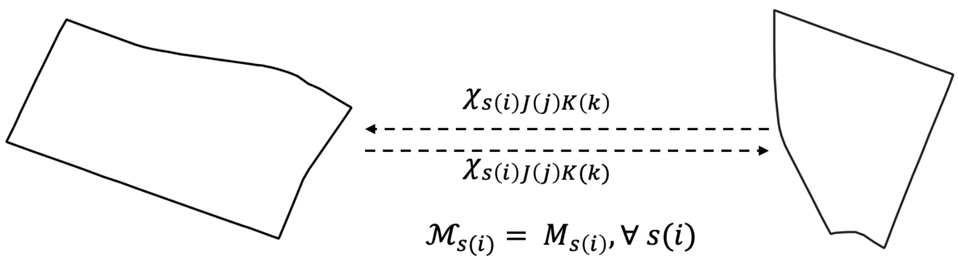
[8]Weighted by commuter frequency, I estimate the average worker's marginal costs of commuting by vehicle total \$1,769 per year.

tract-to-tract pair by adjusting route level preference parameters ($\chi_{s(i)J(j)K(k)}$). Furthermore, $\zeta_{s(i)(m=\text{transit})}$ parameters for the time cost of transit commuting are adjusted endogenously to ensure $\mathcal{M}_{s(i)} = M_{s(i)}$ for each $s(i)$.

Figure 6: Nested Solution Method

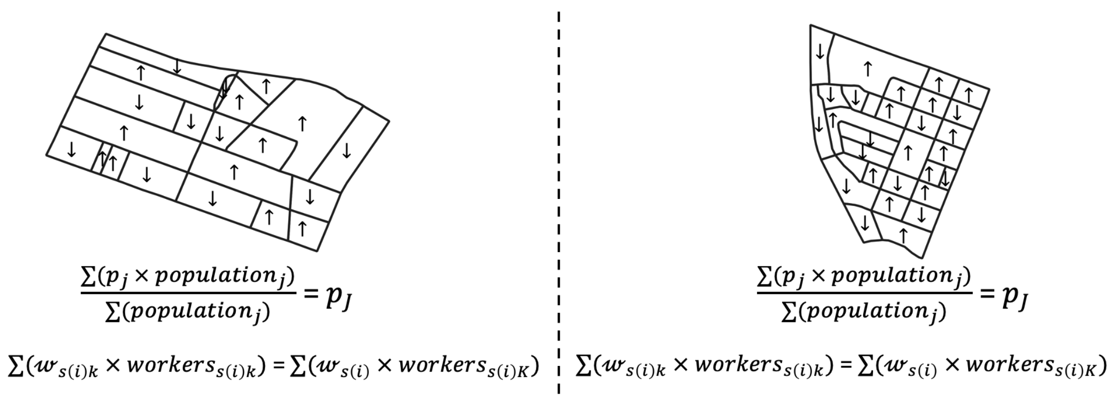
Solving Tract-level Flows and Aggregate Transit Mode Share

- Solve route preference parameters (χ ↑↓) to match bilateral tract flows.
- Solve commute cost parameters ($\zeta_{s(i)(m=transit)}$ ↑↓) to match transit mode share.



Solving Block-level Population Distribution

-Solve block level housing costs (p_j ↑↓) to match block-level resident populations.
-Solve block level wages ($w_{s(i)k}$ ↑↓) to match block-level worker populations.
-Population weighted average housing costs and wages within a tract must equal exogenous tract level rents in initial equilibrium.



The solution method matches tract-level bilateral commuting flows and worker type transit mode share, and also matches within tract population distribution at the block-level. All conditions are solved simultaneously.

Solving for the route level shares requires that each tract is attracting the correct number of residents and the correct number of employed workers. The block-level housing costs (p_j) adjust endogenously to allocate workers in proportion to the population of each block. I restrict the housing cost values such that the average cost faced by a worker within a tract is equal to the tract-level rent calculated from the transaction data ($\frac{\sum(p_j \times \text{population}_j)}{\sum \text{population}_j} = p_{J(j)}, \forall J$). Therefore, matching block-level populations does not have a first order effect on bilateral tract-level route popularity. Similarly, I allow within block wages to adjust so that each block attracts the correct number of workers. I maintain average tract level low- and high-income wages to match the exogenously imposed wage levels ($w_{s(i)=l}, w_{s(i)=h}$).

The model is solved through contraction mapping, with workers selecting a home block, a work block, and a mode, to match tract-level commuter flows, transit mode shares, and block-level populations. I define an equilibrium as the case where low- and high-income worker flows precisely match the observed data, each block has the correct number of residents and workers, worker-type transit mode shares are matched to the data, and workers are in a Nash Equilibrium where they cannot improve their utility by altering any of their home, work, or mode decisions.

The model is identified through matching the observed commuter flows of 94,010 populated tract-level route-by-worker type flows, by adjusting an equal number of endogenous route-by-worker type preference parameters ($\chi_{s(i)jk}$); matching the two observed transit mode share values ($M_{s(i)}$) by adjusting a vector of two endogenous transit time cost parameters ($\zeta_{s(i)v=\text{transit}}$); matching the resident populations of 4,960 blocks by adjusting an equal number of rent values (p_j); and matching the worker populations of 3,218 blocks by adjusting an equal number of wage values ($w_{s(i)k}$).

When solving the model, I identify a unique equilibrium point. Bayer and Timmins (2005) discussed establishing uniqueness specifically for spatial sorting models. A related discussion is provided in Allen et al. (2020). When neighborhood preference is partially determined by the characteristics of other members of the neighborhood (eg preference for neighbor income or race), multiple equilibrium will naturally become a problem. In the current model, I do not consider neighbor preference, which removes concerns over the possible presence of multiple equilibrium.

Identification of parameters in the pre-rail period (Scenario 1) comes from cross-sectional variation in worker choice. If two routes in the model provide the same commute times, housing costs, and wages, the routes will be chosen with equal frequency but for a difference in the preference parameter. To the extent workers in the data prefer one route over the other, the shared idiosyncratic preference parameter is raised to capture any characteristics of the route that might explain its relative popularity. An identifying assumption is that these preference parameters over routes remain fixed, and what changes is the matrix of public transit commute times. A reduction in public transit commute time makes a worker marginally more likely to prefer that route.

Pooling data across eight years and solving commute flows at the tract rather than block-level helps overcome the issue of matrix sparseness and over-fitting identified in Dingel and Tintelnot (2023).[9] O'ahu contains 16 million unique block-to-block commute routes. Using two worker types creates a set of 32 million potential routes. However, 93% of these routes contain zero commuters even after data is pooled. By using tract-level route choices, I estimate the model on a set of 55,440 routes, with two worker types, creating a set of 110,880 potential routes, where only 22% contain no commuters. Among routes with observed workers, the average number of workers is 16, while the median is 2.3.

After solving for a pre-rail equilibrium (Scenario 1), I estimate conditions under counterfactual scenarios. The scenarios are summarized in Table 7. In Scenario 2, I lock in preference parameters, housing costs, and wages and I adjust the matrix of public transit commute times to reflect the opening of the initial nine rail stations. I then recalculate worker commuting times under the improved public transit conditions, holding worker behavior fixed. Subsequently, I allow workers to adjust home location, work location, and mode choice and allow housing costs to adjust to clear the housing market and solve for the new equilibrium under the new commute time matrix (Scenario 3). Offered wages are held constant, but I allow firms to endogenously shrink or grow if they experience a change in labor supply from workers. I calculate solutions in Scenarios 4 and 5 similarly; I apply the commute time matrix that reflects the full rail line operating while holding worker behavior fixed at Scenario 3 levels. Scenario 5 solves the model for a third time through contraction mapping, considering the effects of the full rail system. Providing estimates across the five scenarios is meant to highlight the role of endogenous worker choice, contrast these effects with those under static worker assumptions, and to roughly correspond to the chronological progression of rail construction and worker sorting.

[9] Dingel and Tintelnot (2023) use LODES data for New York City, and demonstrate a significant reduction in estimation bias when pooling three years of data rather than using a single year. I pool eight years of data.

Figure 7: Estimation Scenarios

Scenario 1	Pre-rail.
Scenario 2	Phase 1 rail is completed. Worker choices are held constant at Scenario 1 level.
Scenario 3	Phase 1 rail is completed. Endogenous worker choices.
Scenario 4	Phase 2 rail is completed. Worker choices are held constant at Scenario 3 level.
Scenario 5	Phase 2 rail is completed. Endogenous worker choices.

A description of the scenarios estimated. The locations of Phase 1 and Phase 2 rail stations are shown in Figure 1.

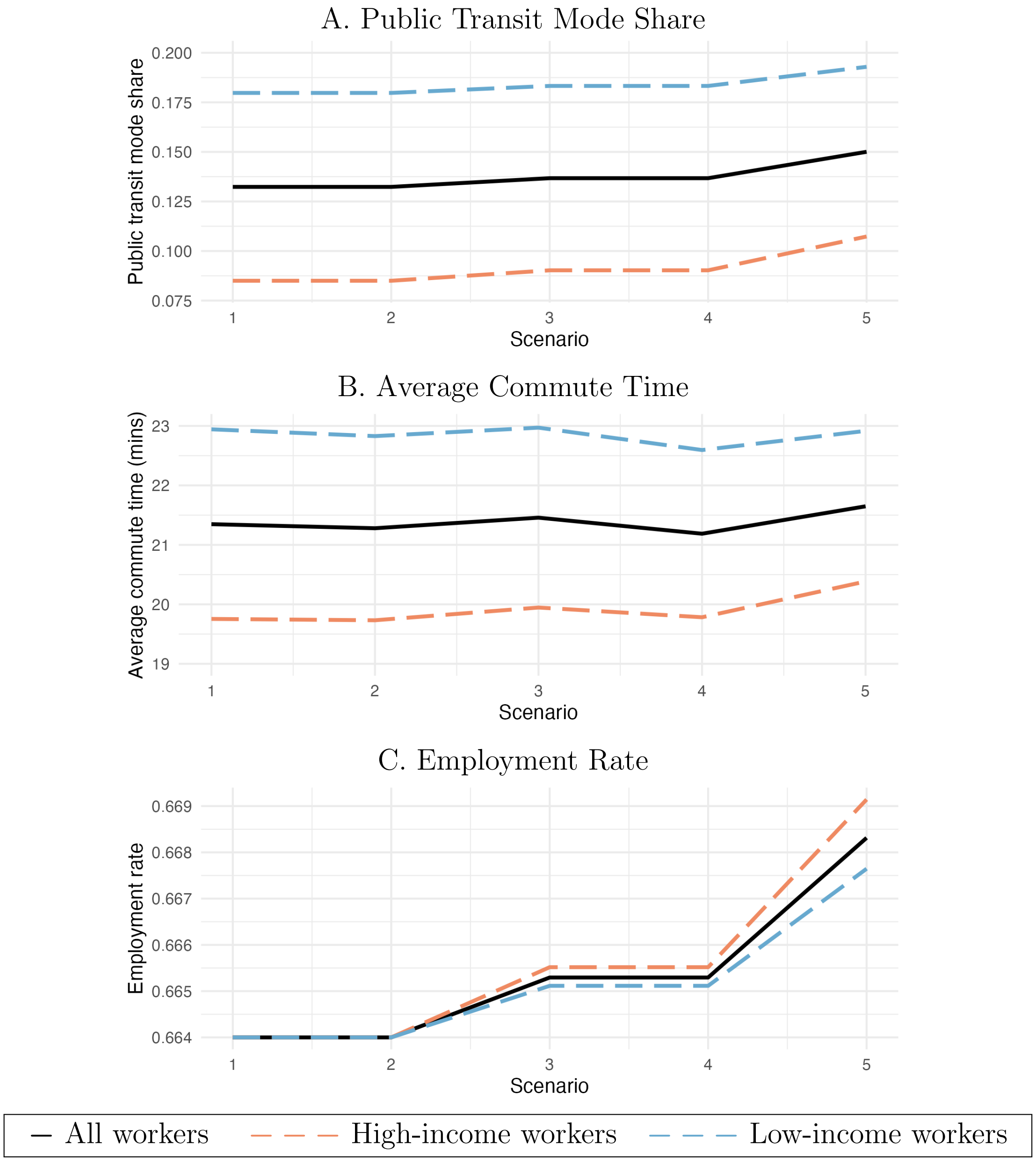
6 Results

I estimate the effect of the rail system on commute times, public transit mode share, and the employment rate. I summarize the three outcomes across scenarios in Figure 8.

Figure 8A shows the progression of public transit mode share. In the pre-rail period, the model matches transit mode share to observed data, with 18.0% of low-income workers using transit and 8.5% of high-income workers using transit. After Phase 1 rail is completed (Scenario 2) and workers are allowed to reoptimize their home, work, and mode-choice decisions (Scenario 3), I find that public transit mode share increases to 18.3% for low-income workers and to 9.0% for high-income workers. I find a larger effect for Phase 2 rail, which provides a rail option for a larger share of commuting routes. After workers reoptimize according to Phase 2 rail (Scenario 5), I find that low- and high-income worker transit mode shares rise to 19.3% and 10.7%, respectively. Comparing Scenario 1 to Scenario 5, I find that the overall public transit mode share rises from 13.2% to 15.0%–a 13% increase. The majority of the improvement (75%) is due to Phase 2 rail. Phase 2 also attracts relatively more high-income workers to public transit, as the Phase 2 stations serve more routes where high-income workers hold a preference.

The Scenario 1 solution shows that the overall average one-way commute time for a low-income worker is 22.9 minutes and that the average for a high-income worker is 19.8 minutes. The changes in commute times are summarized in Figure 8B. The introduction of Phase 1 rail lowers average commute times, as workers who used transit along the

Figure 8: Changes in Aggregate Outcomes



The graphs show the progression of rail's effect on three outcomes. Scenario 1 corresponds to the pre-rail period, while Scenario 5 corresponds to the full rail system with endogenous worker choices. Full scenario descriptions are provided in Figure 7.

rail route benefit from shorter commuting times (Scenario 2). The majority of initial commute time benefits accrue to low-income workers, who are currently the primary users of transit on O'ahu, particularly along the routes served by Phase 1 rail. After the opening of Phase 1 rail, the island-wide average low-income commute time falls to 22.8 minutes (a 0.5% reduction) while high-income average commute time remains virtually unchanged (a 0.1% reduction). Once endogenous worker choices are allowed, the average commuting time improvements are erased. The primary mechanism that causes rail to increase commute times is that transit is a slower mode of transportation, even after the improvements attributable to rail. The increase in public transit mode share (Figure 8A) translates into a rise in average commute time. As a second-order effect, lowering commuting costs presents workers with the opportunity to live farther from their work location, which diminishes the time savings of rail. Additionally, the allocation of rail represents a local amenity to the neighborhoods with rail stations, pushing up local housing costs. Because the location decisions of low-income workers are sensitive to rents, this causes some low-income workers to leave the rail areas for locations with lower housing costs. Low housing cost areas tend to be more peripheral, and often include longer commutes.

In Scenario 4, with the introduction of the full Phase 2 rail line, the commute times for both low and high-income workers fall again. The relative effect on high-income workers is larger in Phase 2 because the location of the new stations align more closely with existing high-income commute flows. After I allow for full endogenous sorting (Scenario 5), I find commute times rise again. In the final equilibrium, I find that average commute time across all O'ahu workers *increases* by 1.4% (or 18 seconds) compared to a scenario where rail was never built. Average commute time for low-income workers falls by a negligible 2 seconds, while average commute time for high-income workers increases by 38 seconds. The introduction of transit systems are often meant to reduce commuting times. It is important to note that when endogenous worker choices are considered, the improvement of public transit infrastructure can raise the average commuting time across the labor market.

The results of this section ignore the possibility that the introduction of rail may reduce driving times by reducing vehicle traffic. In Appendix A, I provide alternative results where I assume driving times are reduced by 5% in the rail corridor. However, I find that the 5% exogenous reduction eliminates 92% of public transit mode-shift identified in the main specification due to induced demand for driving, which suggests that significant reductions in drive times are unlikely to be sustained in equilibrium.

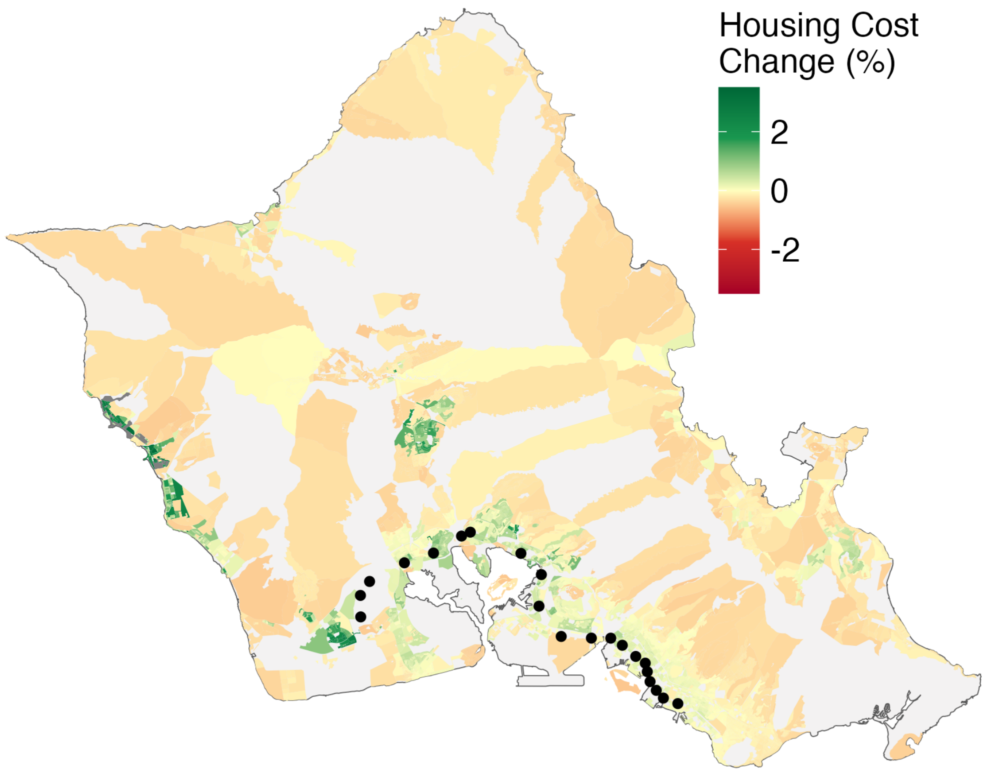
Figure 8C summarizes the aggregate employment effect of rail. High commuting costs are a disincentive to employment. The provision of rail allows a worker to access more employment opportunities for a given amount of commuting costs. Depending on worker idiosyncratic preferences across home location, work location, and mode, the reduced commuting costs will push marginal workers into employment. Across all workers, I find that the full Phase 2 rail system increases the employment rate by 0.4 percentage points–from 66.4% to 66.8%. The change implies that 2,300 workers gain employment in response to the full rail system. The effect is similar among low- and high-income workers. According to ACS data for O'ahu, aggregate annual income is $39 billion, meaning the induced employment effect could generate roughly $254 million in new annual income on O'ahu. Some of this income could be captured by the county and state as tax revenue.

Figure 9 displays the block-level estimated changes in housing cost (p_j) between Scenario 1 and 5. I estimate significant increases in housing costs for blocks near the new rail stations. The block experiencing the largest increase in housing costs sees an increase of 5.6%, while the largest decrease experienced is 0.6%. The cost increases near to stations are largely offset by rent decreases in neighborhoods far from stations, which become comparatively less desirable. I also observe housing cost increases on the far west side of O'ahu and in the central O'ahu neighborhood of Mililani. Both of these neighborhoods have bus service that connects to the new rail system, meaning the rail improves the accessibility from these neighborhoods through the transit network, despite rail not connecting to these areas directly.

7 Conclusion

I estimate the effects of O'ahu's rail system through a QSM. I show that modeling endogenous worker decisions is key to estimating the aggregate effects of the system. By directly modeling worker behavior I am able to provide realistic estimates of aggregate rail impacts. While a common motivation for constructing transit improvements is to reduce commute times, I find that the O'ahu system is likely to marginally increase the average time spent commuting by a worker on O'ahu. However, this is due to the system's success in shifting a meaningful share of the workforce (1.8%) away from private vehicle commuting to public transit commuting. Furthermore, the option of reasonably fast and affordable public transit encourages some workers to enter the labor force. I estimate the full rail system will increase O'ahu's employment rate by 0.4 percentage points by alleviating spatial mismatch.

Figure 9: Estimated Changes in Local Housing Costs



The map shows the predicted housing cost effects of the rail system at the block level. Prices generally increase near rail stations and in places with bus access to rail. Areas with no worker populations are shown in gray. Rail stations are shown as black dots.

One limitation of the model is the assumption of a "closed city." The creation of a valuable public amenity is likely to make workers from outside of O'ahu marginally more likely to move to O'ahu, which may fuel further rent increases around stations and have other second-order effects. Modeling workers as independent agents is also a limitation, as many workers are in dual-earner households and face a more complex location optimization problem.

A complementary policy to rail on O'ahu has been an attempt to generate new housing near rail stations through zoning changes that encourage Transit Oriented Development. I do not model endogenous housing supply responses, and consider this process to be separate from the impacts of rail. Despite these limitations, I believe the paper provides realistic estimates for the probable effects of rail. All of the paper's main results are driven by endogenous worker choices. This highlights the importance of QSMs in evaluating urban transit projects.

This paper contributes to the literature on discrete neighborhood choice modeling, as well as studies on transportation infrastructure evaluation. I analyze a data set with richer spatial variation than has been attempted in any prior related works. Census block-level analysis allows for the model to capture extremely local impacts of rail. Workers are rarely willing to walk significant distances to reach rail. Many studies assume pedestrian catchment areas extend only about 0.5 miles from a station (Guerra et al., 2012). Therefore, the use of larger geographic units will be unable to accurately capture commuter behavior. I propose a method to overcome the issue of commute matrix "sparseness," as defined in Dingel and Tintelnot (2023). The combination of multiple worker types, explicit modeling of transportation costs, and a nested approach to modeling route-level preference parameters and neighborhood choice provides a unique modeling approach that may be helpful for research in other settings.

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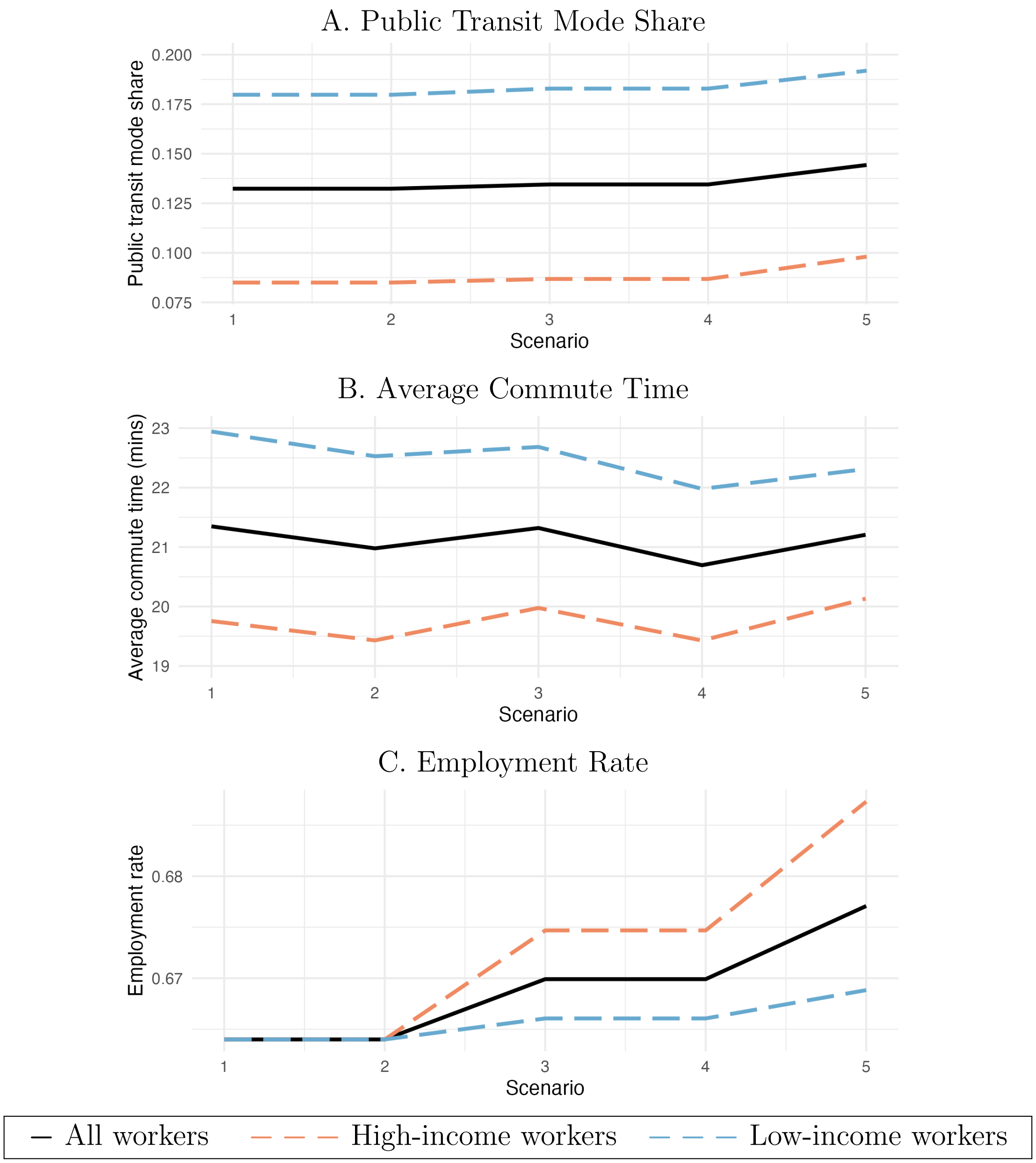
Appendix A

In the main specification I assume the rail line does not affect driving commute times. Overall, the main model suggests rail would reduce the total number of car commuters on O'ahu by 5,700, which is the net effect of a 0.4 percentage point increase in the working population and a 1.8% increase in the public transit mode share. This reduction would be concentrated around the rail lines, which could lead to fewer traffic delays. In Figure A1, I provide results where I assume that vehicle travel times that cross the rail corridor fall by 5% when rail is operating. Under this alternative assumption I find that the full rail line increases public transit mode share by 1.2 percentage points, reduces average island-wide commute time by 8 seconds, and increases the island-wide employment rate by 1.3 percentage points. Without the reduction in drive times (Figure 8), the estimates were a 1.8 percentage point increase in public transit mode share, a 21 second *increase* in average commute time, and a 0.4 percentage point increase in the employment rate.

A reduction in vehicle travel time makes driving marginally less costly, which improves the overall commute time and labor market effects of rail, but reduces the estimated gain in public transit mode share. However, under the 5% time reduction scenario, the reduction in car commuters would be 460 rather than 5,700. The model captures induced demand (Duranton and Turner, 2011), as workers shift into the labor force, and shift towards driving, to take advantage of faster drive times. The model predicts that 92% of the reduction in traffic would be undone by induced demand. The model does not capture workers' propensity to work more days, or substitute towards a rush-hour commute, which would further contribute to induced demand. Therefore, the model predicts that car traffic, and therefore drive times, would be nearly unchanged, which is consistent with the main specification's assumption of no change in drive times.

A1: Changes in Aggregate Outcomes, Assuming 5% Drive Time Reduction in Rail Corridor



The graphs show the progression of rail's effect on three outcomes. Scenario 1 corresponds to the pre-rail period while Scenario 5 corresponds to the full rail system with endogenous worker choices. Full scenario descriptions are provided in Figure 7.