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

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December 2, 2023

[DRAFT, NOT FOR CIRCULATION]

Abstract

The provision of 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 structural model of location and mode choice for 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 due to endogenous worker sorting. Low-income workers on O'ahu capture a significant share of transit's direct benefits because of their relative preference for both transit and the neighborhoods served by rail.

Keywords: Transportation, Transit, Residential Choice, Neighborhood Change, Spatial Mismatch
JEL classification: J20, J60, R13. R23, R40, R58

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*Thank you to the W.E. Upjohn Institute for Employment Research for their support through the Early Career Research Grant program.

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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 due to endogenous worker responses and land market effects. Workers may change their home location, work location, or labor market participation in response to new transit infrastructure. The presence of transit can act as an amenity that raises local land values. All of these mechanisms impact the magnitude and distribution of transit's benefits.

I study the implementation of rail transit on the island of O'ahu, Hawai'i. The first segment of the 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. I propose and estimate a model that tests for these benefits. 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 structural estimation approach, 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 rail produces commute time savings for the average worker. After accounting for endogenous decisions, I find 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 drive 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 where 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. Structural neighborhood models 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 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), and Ahlfeldt et al. (2015).

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 neighbhorhood 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 dataset of travel times from an online wayfinding service. As discussed in Dingel and Tintelnot (2020), urban discrete choice models using granular data can suffer from estimation bias if the observed commute matrix is "sparse," meaning there are relatively few observed commuters relative to the size of the commute matrix being estimated. I provide some innovations on this topic. I propose a new, nested estimation strategy. I reduce matrix sparseness by pooling multiple years of data, and collapsing flow information from the census block to census tract level.[1] However, given the availability of block level information, I then match worker location distributions to specific blocks 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.

[1] A similar tract level pooling approach is taken in Tyndall (2023), but the approach does not utilize block level information.

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 specifically recover estimates of average commuting time, transit mode share and the island-wide employment rate. I find that only accounting for direct commuting cost savings fails to capture the aggregate impact of transit. Workers with strong preferences for using transit are likely to sort towards 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 structural 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 provides results and Section 6 concludes.

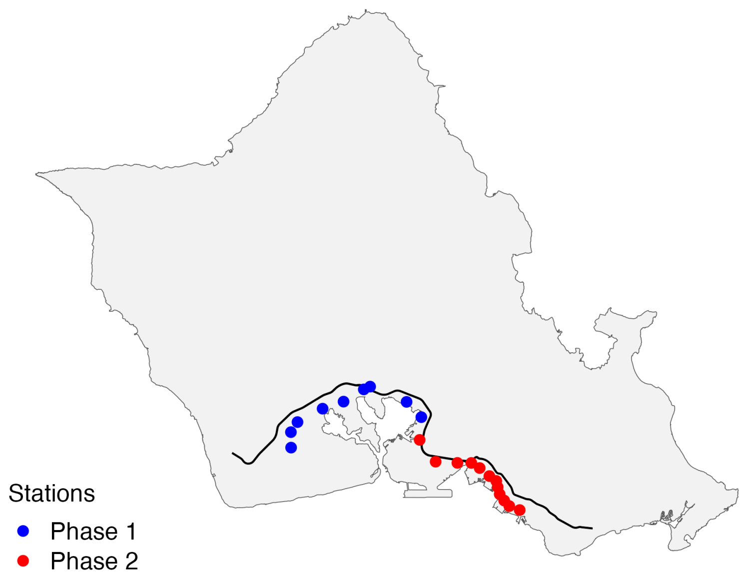
2 Rail Transit on O'ahu

I study the construction 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 Center, a major shopping area in the urban core of Honolulu.[2] The opening of the full 21 station line is set to be completed in stages, with the westernmost nine stations opening in 2023, and the subsequent stations opening by 2031. I will refer to these two sections of the line as Phase 1 and Phase 2 respectively, and provide analysis on the effects of both Phase 1 as well as the full line (Phase 2). 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 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

[2] The precise location of the easternmost stations are the topic of debate and could be revised.

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



The H1 Interstate Highway is shown in black. Phase 1 stations are scheduled to open in 2023. Phase 2 stations are scheduled to open by 2031.

as a partial motivation for providing a 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.

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, mayoral campaigns since 2005 have 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 corridor served by rail 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.[3] 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 is 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 pre-existing rail system.

O'ahu shares many urban form characteristics with mid-sized 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 US. The pre-rail 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.

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

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

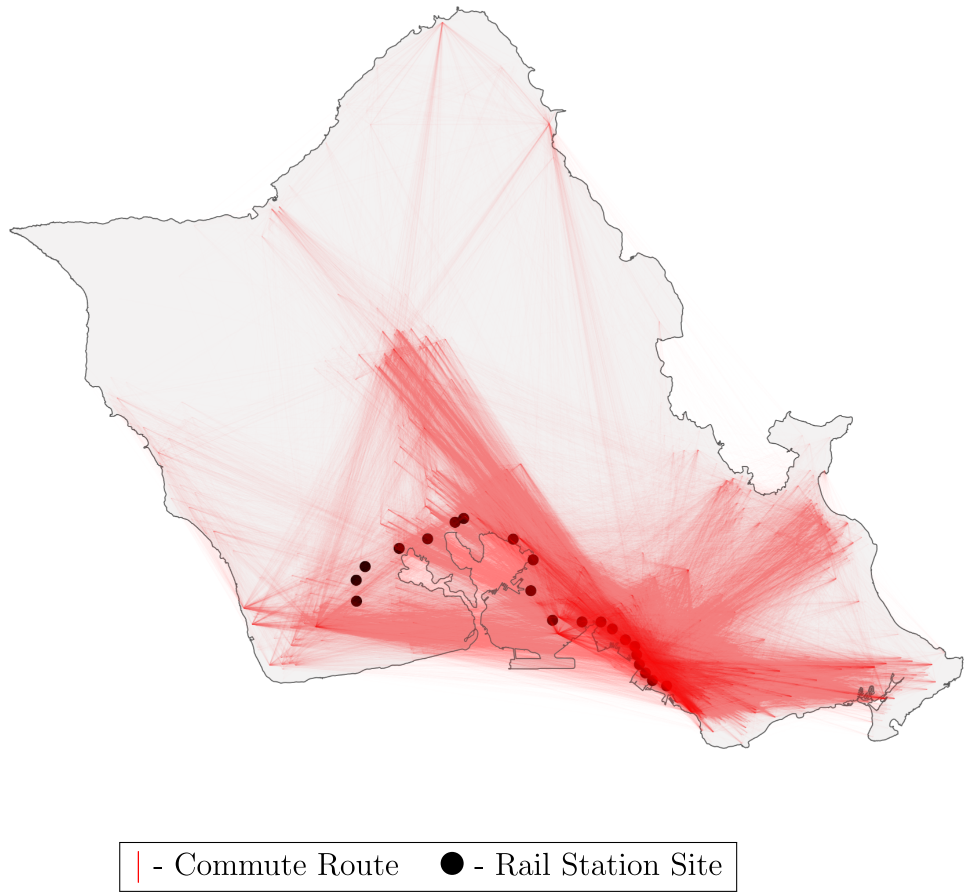
Data are from the 2020 5-year American Community Survey.
† Bachelor's degree or above, among population 25 years and older.

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 earn more than this amount. Across the 2014-2021 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 data the a cross-sectional matrix, where the number of commuters using a route is the average across the 2014-2021 period. Figure 2 maps 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: Commuter Flows



Each line connects a worker's home and work location. Heavier lines indicate 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 Programming Interface (API) returned an estimate of the commuting time. I queried the API for each travel route in the choice set. 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 the 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 collect a full travel time matrix, which reflects conditions that include 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 should better capture spatial access to transit nodes, which can be obscured when using tract centroids.

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 distance is 15 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. After the first phase of rail is completed, I estimate the average public transit commute time across all workers falls by 1.3 minutes. The average commuting times calculated with Travel Time data are comparable to estimates from the American Community Survey (ACS) reported for O'ahu.

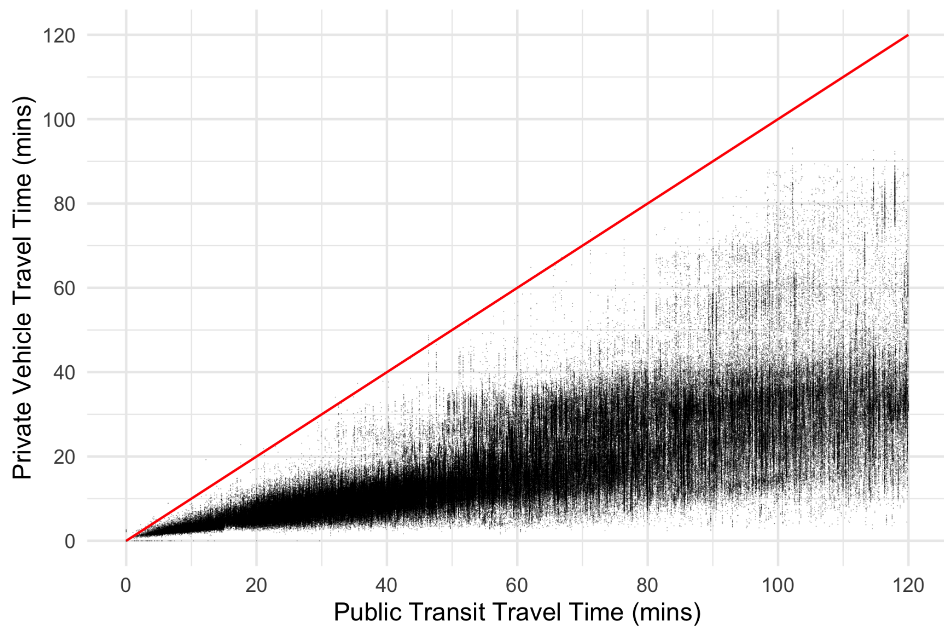
Table 2: Summary Statistics, Route Level Data

	All Observed Routes		Weighted by Workers	
	Driving	Transit	Driving	Transit
Average time, pre-rail (mins)	23.0	62.6	19.5	54.7
Average time, post-Phase 1 rail (mins)	23.0	61.0	19.5	53.4
Average road distance (kms)	18.5	.	15.0	.

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 2-hours one-way.

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 every route, 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 3: Drive Times vs Public Transit Times for Observed Commute Routes, Before Rail

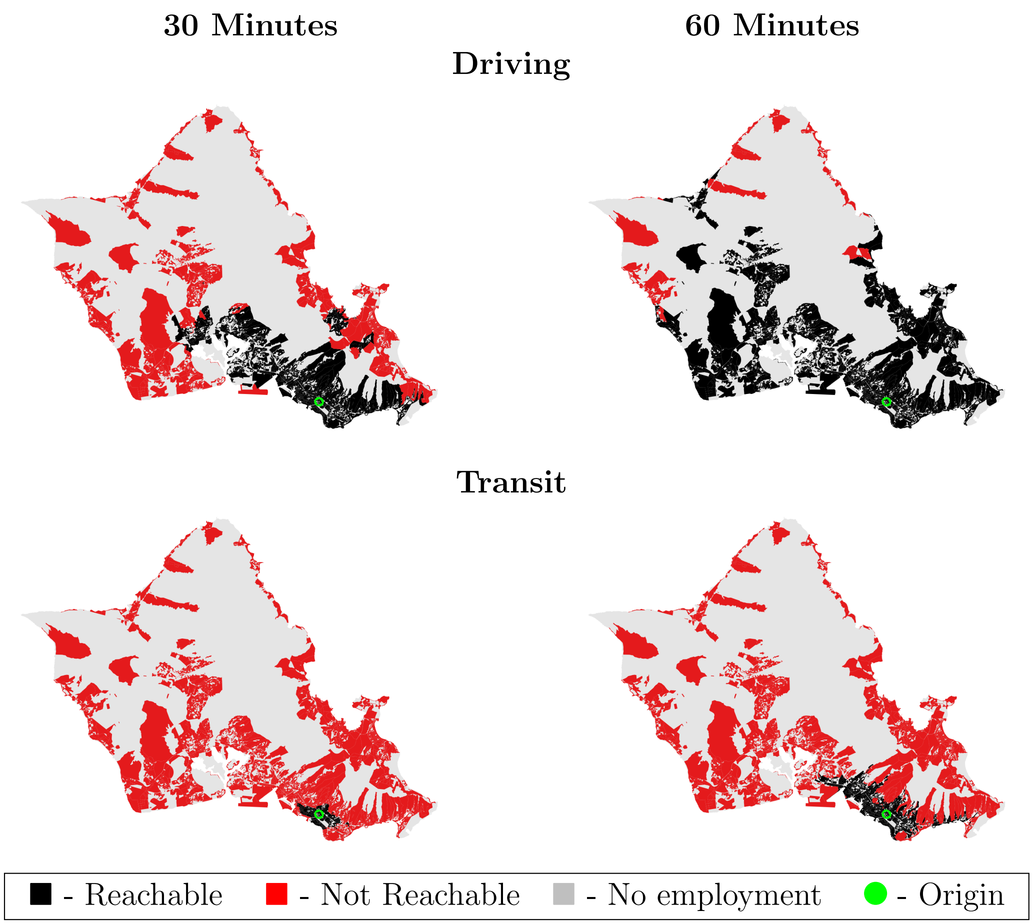


Each point represents one commuting route. The red line would indicate trips where private vehicle and transit commute times are equal. The figure displays all routes that can be completed in under two hours by both driving and public transit (569,339 observations).

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 pre-rail 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 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 driving provides dramatically more job opportunities to a worker when compared to using public transit. The displayed data captures the pre-rail period.

Figure 5 displays the reduction 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. 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 two by first calculating the average reduction in public transit commuting time experienced by any route where the striaght line connection between origin and destination bisect a the phase one rail corridor, where the corridor is defined by as the area within two km of the original 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.

The model will incorporate estimates of local housing costs as a parameter. I approximate annualized local housing costs for each census block in the model. I use Multiple Listings Service (MLS) data for O'ahu. The data covers every real estate transaction in the MLS from 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 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 value of $34,975 (or $2,915 per month). 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 demographic information, such as the employment rate. For this demographic information I use 2020 5-year ACS.

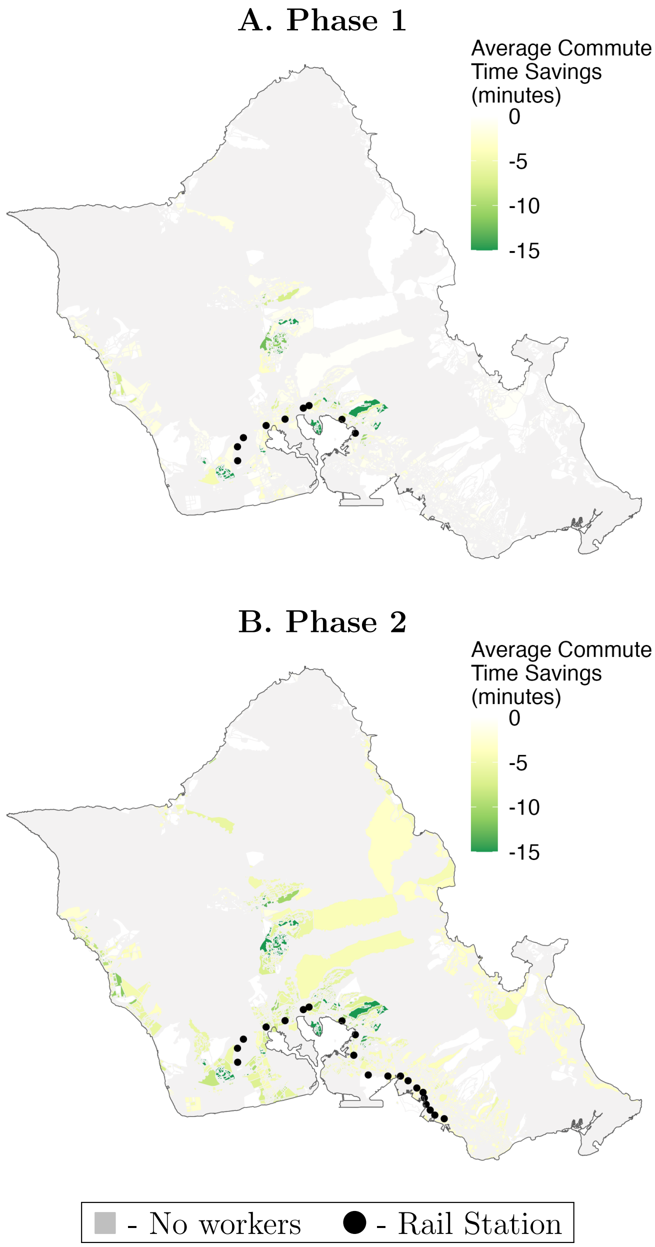
4 Methodology

I propose a structural neighborhood choice model to predict the effects of the new rail system on (1) 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 monocentric city model. Workers are utility maximizing and face a trade-off between housing costs and commuting costs. 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 which governs worker preferences.

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 average commuting time difference across all block-to-block pairs for public transit routes.

$$U_{ijkv} = (C - c_{s(i)jkv})^{\gamma}_{s(i)} H^{(1-\gamma_{s(i)})} \chi_{s(i)jk} \xi_{ijkv} \tag{1}$$

Workers derive utility from numeraire consumption (C) and the consumption of generic units of housing (H). Non-monetary commuting costs (c) reduce consumption utility. Each worker (i) chooses a home location (j), work location (k), and mode of transportation (v). Mode choice is limited to driving or 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. $s(i)$ determines the income level of the worker when they are employed and this characteristic is fixed.

$\chi_{s(i)jk}$ is a route and worker type specific preference parameter. 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. A Type 1 extreme value distributed error term (ξ_{ijkv}) captures the worker specific idiosyncratic preferences over each available route-mode option.

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

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

Each worker operates under a budget constraint, represented by equation 3. Workers exhaust their income[4] ($w_{s(i)k}$) on housing costs (Hp_j), numeraire consumption (C), and monetary commuting costs (θ_{jkv}). Monetary commuting costs will be calculated according to the mode selected and 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).

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

A worker's income is set according to their type, except in the case where a worker chooses a null work location ($k = \emptyset$), which represents being out of the labor force.

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

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, show in Equation 4.

$$V_{ijkv} = (w_{s(i)k} - c_{s(i)jkv} - \theta_{jkv})\gamma_{s(i)}{}^{\gamma_{s(i)}} \frac{1-\gamma_{s(i)}}{p_j}^{1-\gamma_{s(i)}} \chi_{s(i)jk}\xi_{ijkv} \tag{4}$$

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

$$P_{ijkv} = \frac{e^{V_{ijkv}}}{\sum_1^{\bar{j}} \sum_1^{\bar{k}} \sum_1^{\bar{v}} e^{V_{ijkv}}} \tag{5}$$

I calculate the total public transit mode share by summing all of the choice probabilities where v is public transit and dividing by the total sum of choice probabilities. I will refer to the true (observed) public transit mode share as $M_{s(i)}$ and the model generated value as $\mathcal{M}_{s(i)}$.

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

5 Solution Method

My approach differs from prior literature in two main ways. First, I have access to a block level matrix of before and after commuting times, which allows for a more granular analysis than has been possible previously. Second, to accommodate granular data without succumbing to the overfitting issues identified in Dingel and Tintelnot (2020) I propose a new method of nesting a block level neighborhood choice model within a tract level model solved by matching tract level bilateral commuter flows.

I first solve the complete 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, mode choice, and a vector of route by worker type preference parameters. I then use these parameters to run four counterfactual scenarios, which capture conditions across various rail and worker sorting conditions as described below.

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.[5] 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
$\zeta_{v=\text{driving}}$	0.93	Commuting cost per unit time as share of wage, driving
$\theta_{jk(v=\text{transit})}$	0.96	Annual monetary cost of transit commuting (\$1,000)
$\theta_{jk(v=\text{driving})}$	$0.0589 \times \mathrm{d}_{jk}$	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 5-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.[6] I use these estimates to parameterize γ.

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 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.

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

[5] I use individual wage earnings from the 2020 5-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.

[6] 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.

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 ($\zeta_{s(i)v=\text{transit}}$) 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 costs \$960 in Honolulu ($\theta_{jk(v=\text{transit})} = 0.960$). For those driving, I approximate monetary commute costs using data from the American Automobile Assosiation (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.[7] 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 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 through contraction mapping. Route level idiosyncratic parameters, which are defined by census tract pairs, adjust to attract the precise number of workers of each income type as are recorded in the data. Furthermore, $\zeta_{s(i)v=\text{transit}}$ parameters for the time cost of transit commuting are adjusted endogenously to ensure $\mathcal{M}_{s(i)} = M_{s(i)}$ for each $s(i)$.

Solving for the route level shares entails that each tract is attracting the correct number of total workers. Within tracts, I match block level worker populations. The housing costs (p_j) adjust endogenously to attract the correct number of resident workers. I restrict the rent levels such that the average rent within a tract is equal to the tract level rent calculated from the MLS data. Therefore, matching block level populations

[7] Weighted by commuter frequency, I estimate the average cost of commuting by vehicle to be \$1,769 per year.

does not have a first order effect on bilateral tract level route popularity.

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 worker residents, 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 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 ($\zeta_{s(i)v=\text{transit}}$), and matching the worker populations of 4,960 blocks by adjusting an equal number of rent values.

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. Holding other factors constant, if two routes in the model provide the same commute times, the routes will be chosen with equal frequency. 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.

After solving for a pre-rail equilibrium (Scenario 1), I estimate conditions under counterfactual scenarios. The scenarios are summarized in Table 6. In Scenario 2, I lock-in preference parameters and rents 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 rents to adjust to clear the housing market and solve for the new

Figure 6: 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.

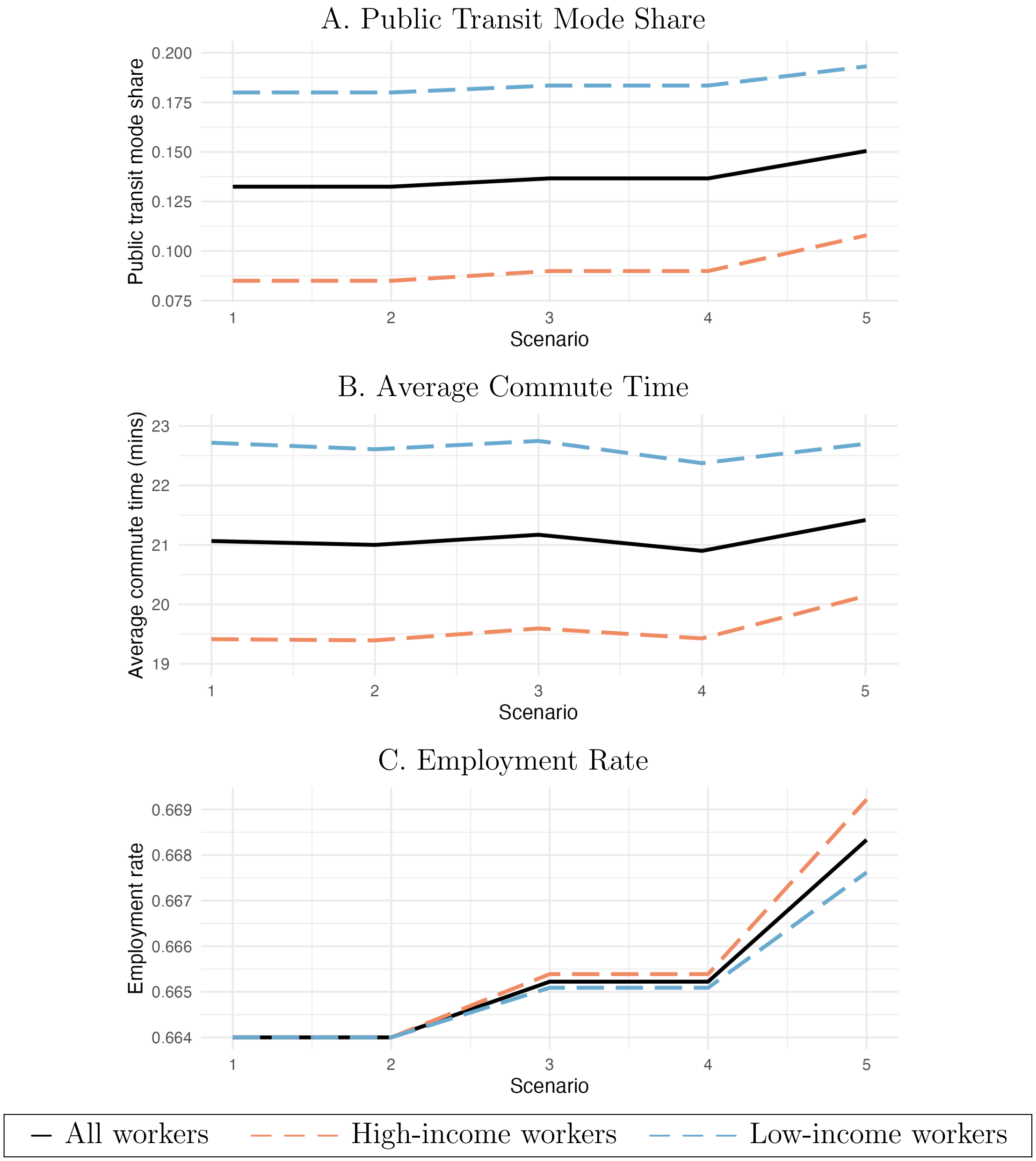
equilibrium under the new commute time matrix (Scenario 3). Offered wages are held constant, but I allow firms to endogenously shrink or grow if they experience a change in labor supply from workers. I calculate Scenario 4 and 5 solutions similarly. I first reduce public transit travel times for routes that intersect the Phase 2 rail area but did not intersect Phase 1 and recalculate commuting times 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.

6 Results

I am primarily interested in estimating 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 7.

Figure 7A 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 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

Figure 7: 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 6.

commuting routes. After workers reoptimize according to Phase 2 rail (Scenario 5) I find low and high-income worker transit mode shares rise to 19.3% and 10.8% respectively. Comparing Scenario 1 to 5, I find that the overall public transit mode share increases from 13.2% to 15.0%, a 14% increase. The majority of the improvement (77%) occurs on account of 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 average one-way commute time for a low-income worker is 22.7 minutes while the average for a high-income worker is 19.4 minutes. The changes in commute times are summarized in Figure 7B. The introduction of Phase 1 rail lowers average commute times as workers who used transit along the 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, island-wide average low-income commute time falls to 22.6 minutes (a 0.5% reduction) while high-income average commute time remains virtually unchanged (a 0.1% reduction). Once endogenous worker choices are allowed, all of the commuting time gains are erased. The primary mechanism that causes rail to result in higher 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 7A) translates to a rise in average commute time. As a second order effect, the allocation of rail represents a local amenity to the neighborhoods with rail stations, pushing up local housing costs. Because the location decision of low-income workers are sensitive to rents, this causes some low-income workers to leave the rail areas for locations of lower housing costs. Low housing cost areas tend to be more peripheral, and often include longer commutes. Generally, lowering commuting costs presents workers with the opportunity to live farther from their work location, which diminishes the time savings of rail.

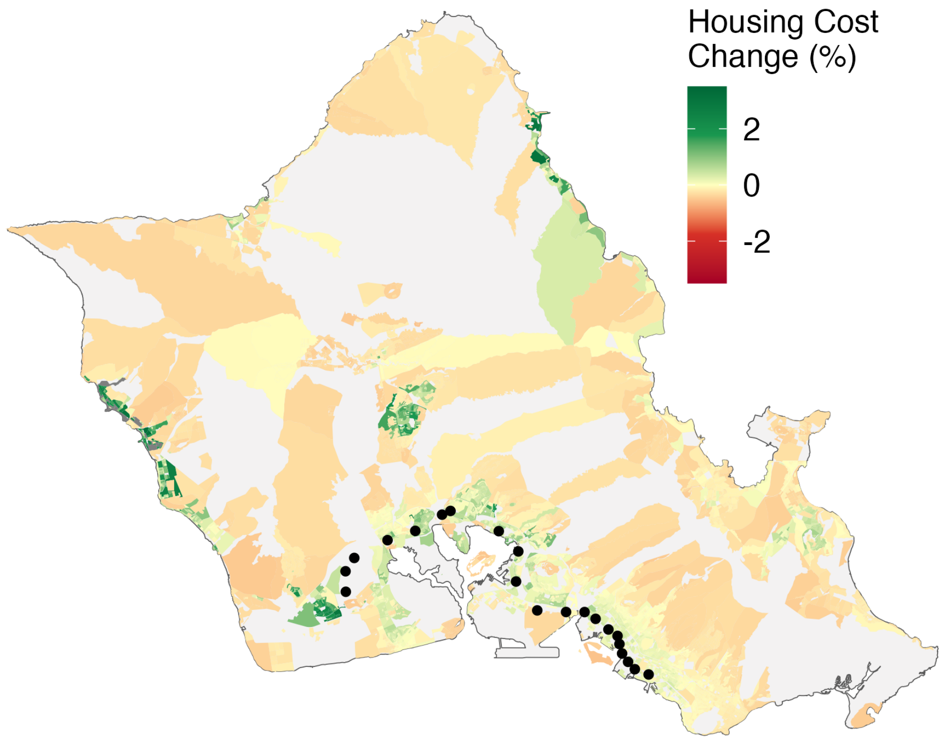
In Scenario 4, with the introduction of the full Phase 2 rail line, both low and high-income commute times fall again. The relative effect on high-income workers is larger in Phase 2 because the location of the new stations align more closely with existing high-income commute flows. After I allow for 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 1.7% (or 21 seconds) compared to a scenario where rail was never built. 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. While I do not account for potentially improved traffic conditions due to mode switching away from private vehicles, in the long run, induced demand suggests that private vehicle time savings will be negligible (Duranton and Turner, 2011).

Figure 7C summarizes the effects on the share of workers who are employed. 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 the full Phase 2 rail system increases the employment rate by 0.4 percentage points from 66.4% to 66.8%. The effect among low-income workers is a 0.4 point increase whereas the effect on high-income workers is 0.5 points.

Figure 8 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 to the new rail stations. The block experiencing the largest increase in housing costs sees an increase of 5.4%, 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.

Some interesting substitution patterns emerge from the model. For example, I find price increases in the O'ahu neighborhood of Kailua, located in the north-east section of the island, despite Kailua being far from rail. Routes originating from Kailua have high preference parameters among high-income workers. The substitution pattern is consistent with high-income workers moving away from rail neighborhoods towards Kailua. High-income workers are less likely to use rail but would still need to pay the higher housing costs associated with increased neighborhood demand. Therefore, rail may push out high-income workers and cause them to select alternative neighborhoods which match their preferences. 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.

Figure 8: 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 fall elsewhere. Areas with no worker populations are shown in grey. Rail stations are shown as black dots.

7 Conclusion

I estimate the effects of O'ahu's rail system through a neighborhood choice model. 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.

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, which highlights the importance of urban neighborhood choice modeling in evaluating urban transit projects. This paper contributes to the literature on discrete neighborhood choice modeling and related 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 incentives. I propose a method to overcome the issue of commute matrix "sparseness," as defined in Dingel and Tintelnot (2020). 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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