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Predicting Rail Transit Impacts with Endogenous Worker Choice: Evidence from Oahu

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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 because of endogenous worker decisions. I examine a large public-transit rail project on the island of Oahu, Hawaii. Using block-level commuter-flow and travel-time estimates, I propose and estimate a quantitative spatial 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, because of endogenous worker sorting. Low-income workers on Oahu capture a significant share of transit's direct benefits because of their relative preference for both transit and the neighborhoods served by rail.

JEL Classification Codes: J20, J60, R13, R23, R40, R58

Key Words: transportation, transit, residential choice, neighborhood change, spatial mismatch

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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. 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 have an impact on the magnitude and distribution of transit's benefits.

I study the implementation of rail transit on the island of Oahu, Hawaii. The first segment of the system began operating in 2023. The proposed benefits of building rail on Oahu 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 quantitative spatial model (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 Oahu, as workers substitute away from cars and toward transit, and as they also substitute toward longer routes. Despite this failing to reduce average commute time in spatial equilibrium, I find that 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 United States. 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 generally 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 was 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 the 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 U.S. cities, and Chernoff and Craig (2022) examined the 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 way-finding 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.[1] However, given the availability of block-level information, I then match worker location distributions to specific blocks within tracts by nesting a housing market within tracts.

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

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 specifically 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 be either to attract or to 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.

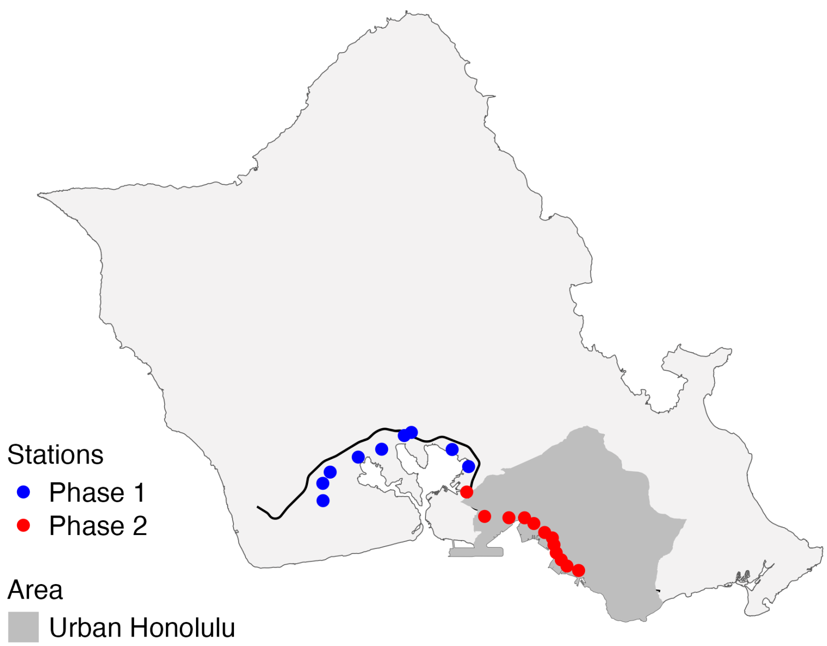
2 Rail Transit on Oahu

I study Oahu'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 kilometers—about 19 miles. The western edge of the system extends to the Kapolei neighborhood, and the easternmost station is located at Ala Moana Center, a shopping mall and major mixed-use area in the urban core of Honolulu for dining and entertainment.[2] The opening of the full 21-station line is set to be completed in stages, with the westernmost 9 stations opening in 2023, the subsequent 10 stations opening by 2031, and the final 2 opening at an unconfirmed

[2]The precise location of the easternmost stations is a 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.

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 on the effects of the full line (Phase 2). Figure 1 shows the locations of the rail stations on the island of Oahu.

Figure 1: Location of Rail Stations on Oahu and the H1 Highway



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

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. Eastbound traffic on the H1 is heavy during rush hour; this fact served as a partial motivation for providing a high-capacity public transit option on this route. Household incomes on the west side of Oahu are generally lower than on the east side of Oahu, 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 Oahu 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 from 2004 to 2020 have debated whether to complete or abandon construction of the rail line. Political opposition to the construction of rail often centered on concerns about cost overruns. When construction began, capital costs were expected to be $4 billion, with $1.6 billion coming from the Federal Transit Administration (FTA). However, 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 United States (Brooks and Liscow, 2022; Gupta et al., 2022), the Oahu system's construction costs are extremely high relative to similar projects in 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. Oahu provides relatively extensive bus service compared to similar-sized U.S. cities. However, buses travel within general traffic in almost all cases, meaning they are subject to traffic delays and the accompanying uncertainty about trip duration.

The island of Oahu is coterminous with the City and County of Honolulu.[3] Oahu 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 Oahu, the boundaries of the study area are clear, and there are no border-area spillover effects to be considered. Access to Oahu from the neighboring Hawaiian Islands is only possible by air travel. Oahu 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 U.S. metropolitan areas.

Second, the Oahu 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.

Oahu shares many urban-form characteristics with midsized American cities, such as significant highway infrastructure and primarily single-family-zoned land use, sur-

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

rounding a relatively dense urban core. Demographics on Oahu are unique in several dimensions: Median household income on Oahu ($87,700) is higher than the median household income across U.S. metropolitan areas ($69,600), while the college education rate is similar. Oahu has a high Asian population share (43 percent) and a high share of Native Hawaiians and Pacific Islanders (10 percent) when compared to other metropolitan areas in the United States. The pre-rail rate of public transit commuting on Oahu (7.2 percent) was about 40 percent higher than the average rate across other metro areas. Demographic information for the study area is provided in Table 1, with comparisons to average U.S. metro conditions and the United States as a whole.

Table 1: Demographic Characteristics of Study Area

	Oahu	**U.S. metro areas**	**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 (yrs)	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

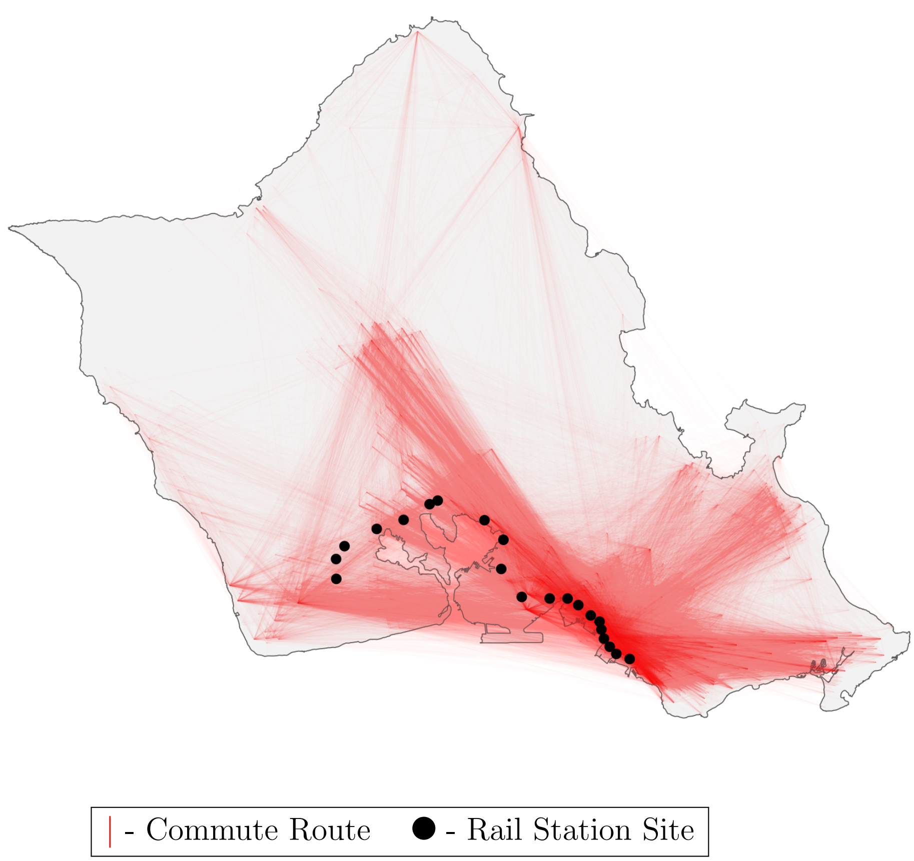
SOURCE: Data are from the 2020 five-year American Community Survey.
† Bachelor's degree or above among population 25 years and older.

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 U.S. 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. 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 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 Oahu's workers commute within the corridor that will be served by rail.

Figure 2: Block-to-Block Commuter Flows



NOTE: Each line connects a worker's home and work location. Heavier shadings 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 programming interface (API) returned an estimate of the commuting time. I queried the API for every block-to-block route on Oahu. 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 workers to get to their destinations by 9:00 a.m. on a Wednesday in order to match likely commuting times. I use the geographic centroid of each census block as the origin and destination points, and I 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 posttreatment 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 kilometers (km) from the geographical centroid of its 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 local 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 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 Oahu.

Table 2: Summary Statistics, Route-Level Data

	All Observed Routes		Weighted by Workers	
	Driving	Transit	Driving	Transit
Average road distance (kms)	18.5	.	15.0	.
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 time, post-Phase 2 rail (mins)†	23.0	57.9	19.5	50.7

NOTE: Average route characteristics among observed commutes on Oahu. 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 method described in this section.

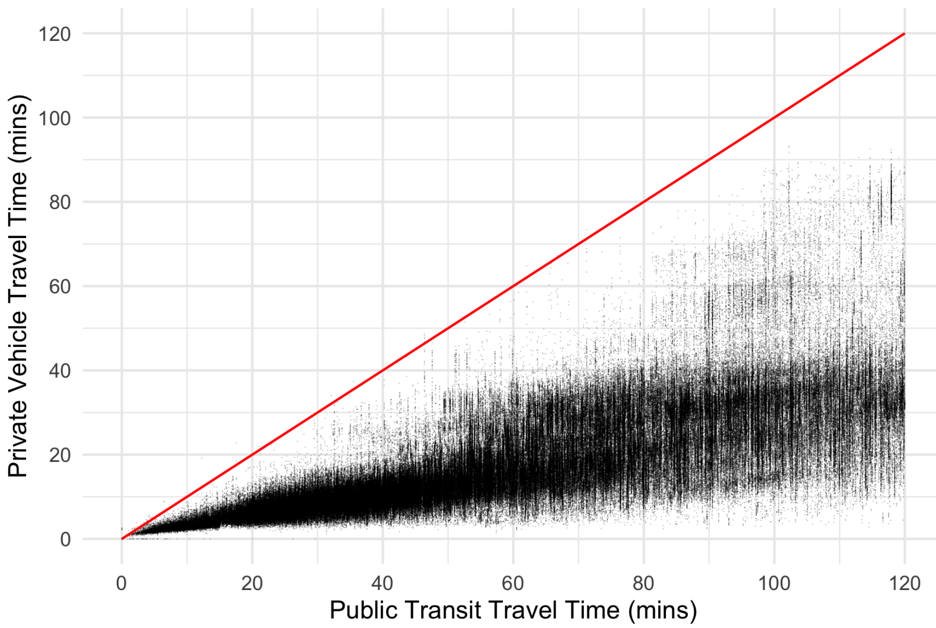
Figure 3 shows the relationship between driving times and public transit times for the data covering the period before the rail system was running. For nearly every route, driving provides a shorter trip time than public transit. For 96.3 percent of routes, public transit takes more than twice as long as driving; for 74.7 percnt of routes, transit takes more than three times as long, and for 48.8 percent 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 Oahu that are more than two hours apart by driving.

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

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

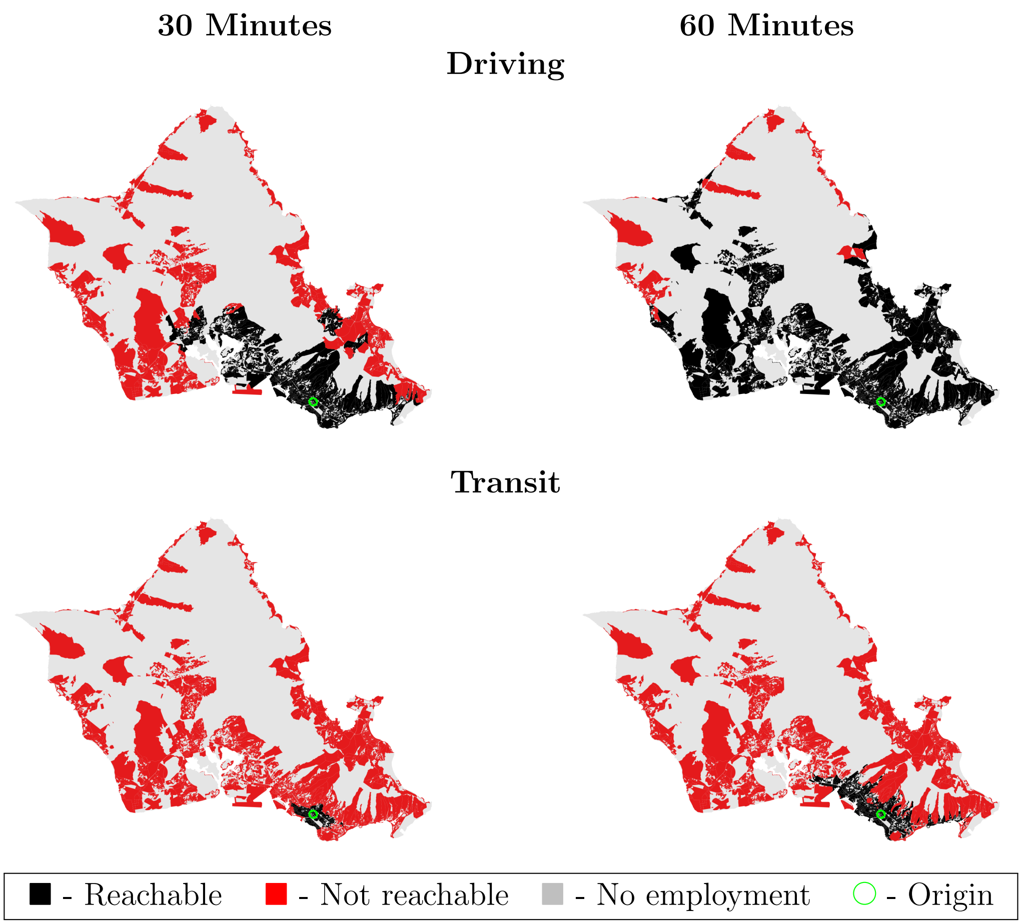


NOTE: Each point represents one commuting route. The red line would indicate trips where private vehicle and transit commute times are equal. The figure displays all routes that can be completed in under two hours by both driving and public transit (569,339 observations).

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, in which the corridor is defined as the area within two kilometers of the rail line. I find that the average route bisecting the Phase 1 corridor experienced a 6.0 percent reduction in public-transit commuting time. I apply this measure to Phase 2 by reducing public-transit commute times by 6.0 percent for any route that bisects the Phase 2 rail corridor.

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 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 tracts. For every route, I assume that the post-rail travel time is the minimum of the observed pre- or post-rail time. I also assume that transit-time reductions occurred

Figure 4: Job Locations Accessible from One Origin Location

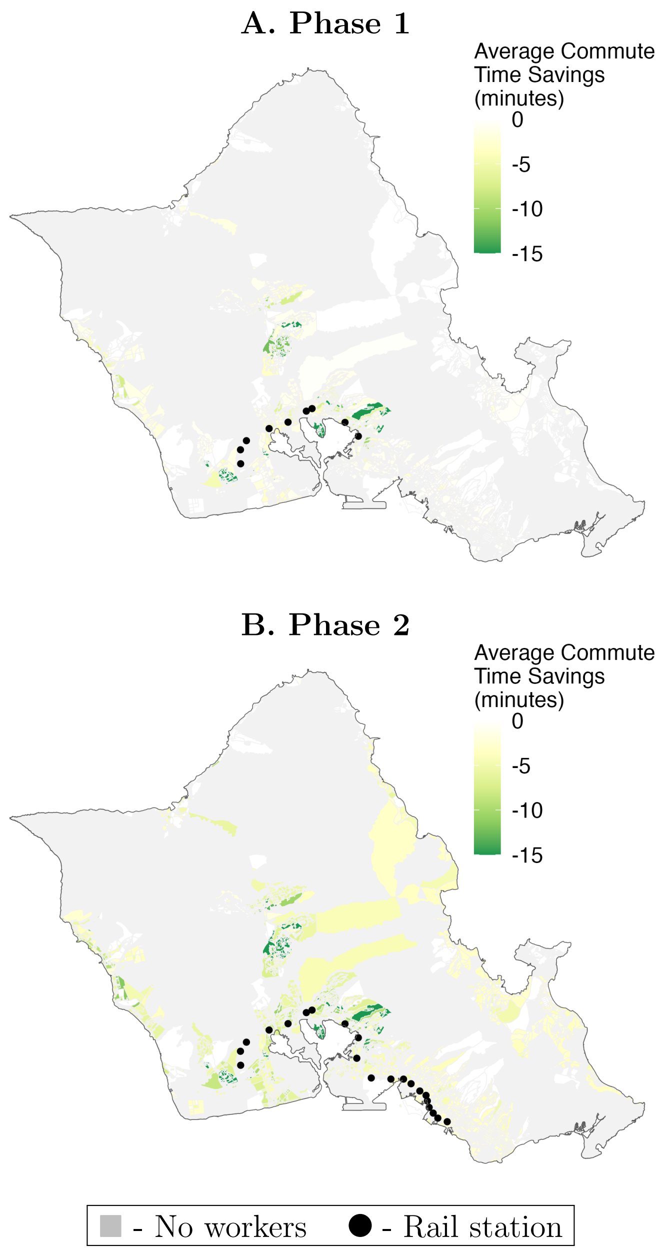


NOTE: Block-level information is presented, showing which areas are reachable through driving and public transit from an origin location placed in Honolulu's city center. I find that driving provides dramatically more job opportunities to a worker compared to using public transit. The displayed data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

only 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 block in the model. I use deed transfer records from Oahu. The data cover every real-estate transaction from 2010–2021. I calculate the median sale 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 the block level to reduce noise in areas with few transactions. Estimated annual housing costs

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



NOTE: 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.

calculated in this way range from \$11,750 to \$137,397, with a median value of \$34,975 (or \$2,915 per month).[4] Because the model encompasses both renters and owners, this

[4] 2021 five-year ACS data record median monthly housing costs for owner-occupiers on Oahu to be

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 the 2020 five-year ACS.

4 Methodology

I propose a structural neighborhood-choice model 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. 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:

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

Workers derive utility from numeraire consumption (C) and generic units of housing (H). Nonmonetary commuting costs (c) reduce consumption utility. 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. $s(i)$ determines the income level of the worker when that worker is 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

$2,800, closely matching the median calculated from the deed transfer records.

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 toward routes that provide higher utility to their type, on average. A Type 1 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 various worker types may have different preferences across modes. $\omega_{s(i)k}$ denotes hourly wage. τ_{jkm} represents the annual 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. 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's income is set according to the worker's type, except in the case where a worker chooses a null work location ($k = \emptyset$), which 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 ($w_{s(i)k}$) and hourly wage ($\omega_{s(i)k}$) are related, assuming an eight-hour workday and 260 working days in a year: $w_{s(i)k} = \omega_{s(i)k} \times 8 \times 260$.

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

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

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

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. 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 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 of nesting a block-level neighborhood choice model within a tract-level route choice model, solved by matching tract-level bilateral commuter flows and subsequently matching block-level population distributions.

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 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.[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

NOTE: I impose these parameters on the model.

I assume that an individual worker spends a constant fraction of income on housing $(1-\gamma)$. Using Oahu-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 that low-income workers spend 47 percent of their income on housing and that high-income workers spend 15 percent of their 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 at the tract level, according to the tract-level estimates from MLS 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 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 U.S., finding that the average worker spends 24 percent of his or her income on housing.

in Los Angeles, finding that drivers faced a time cost of driving equal to 93 percent 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 percent for low-income workers and 8.5 percent for high-income workers. To avoid introducing an additional mode choice, I consider walking to be a component of public transit. Notably, public-transit-mode share among the low-income group is more than twice that of the high-income group. When solving for 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 that workers pay for 12 monthly transit passes each year, which cost \$960 in Honolulu ($\theta_{jk(v=\text{transit})} = 0.960$), prior to the rail opening. 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 I 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 percent). I assume worker nonparticipation is equally likely across worker types.

The model has a nested solution method, illustrated in Figure 6. Bilateral commuter flow counts for each worker type are matched for every tract-to-tract pair by

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

adjusting route-level preference parameters ($\chi_{s(i)J(j)K(k)}$). For notation, 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 $K(k)$. 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 $s(i)$.

I simultaneously solve for block-level worker populations. Solving for the route-level shares requires that each tract is attracting the correct number of resident workers. The block-level housing costs (p_j) adjust endogenously to allocate workers in proportion to the population of each block. I restrict the rent values so that the average rent faced by a worker within a tract is equal to the tract-level rent calculated from the MLS 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.

The model is solved through contraction mapping to match tract-level commuter flows, transit-mode shares, and block-level populations. I define an equilibrium as the case in which 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 for which 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 (p_j).

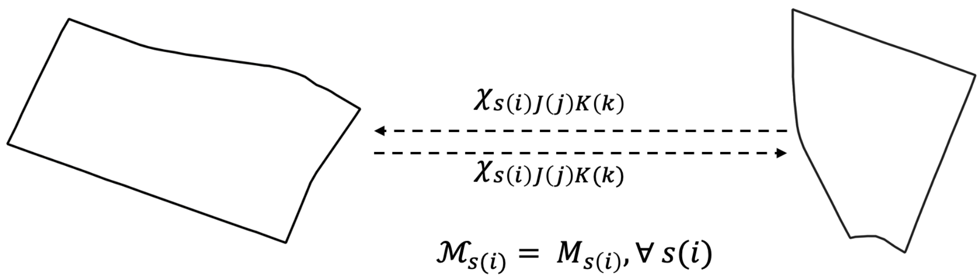
When solving the model, I identify a unique equilibrium point. Bayer and Timmins (2005) discussed establishing uniqueness specifically for spatial sorting models. A related discussion is provided in Allen et al. (2020). When neighborhood preference is partially determined by the characteristics of other members of the neighborhood (e.g., 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 equilibria.

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 and housing costs, the routes will be chosen with equal frequency but for a difference in the preference parameter. To the extent that workers in the data prefer one route over the other, the shared idiosyncratic preference parameter is raised

Figure 6: Nested Solution Method

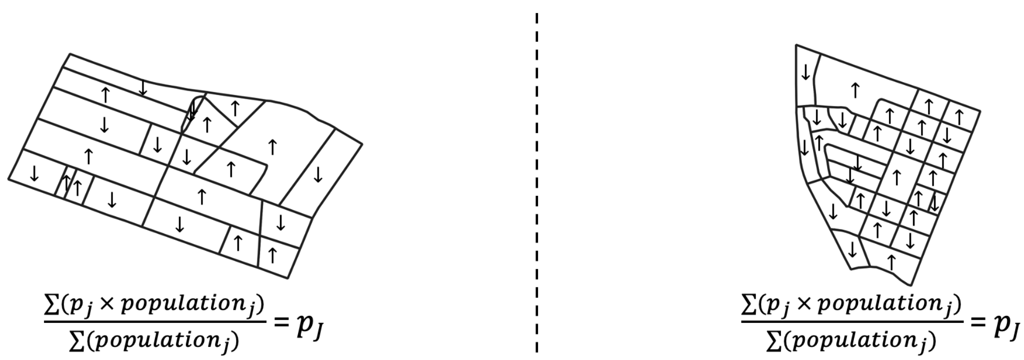
Solving Tract-Level Flows and Aggregate Transit-Mode Share

Solve route parameters ($\chi \uparrow\downarrow$) to match bilateral tract flows.
Solve commute cost parameters ($\zeta_{s(i)(m=transit)} \uparrow\downarrow$) to match transit-mode share.



Solving Block-Level Population Distribution

Solve block rents ($p_j \uparrow\downarrow$) to match block-level populations within tracts.



NOTE: 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. The conditions are solved simultaneously.

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 level rather than the block level helps overcome the issue of matrix sparseness and overfitting identified in Dingel and Tintelnot (2023).[9] Oahu contains 2.5 million unique block-to-block commute routes across two worker types, creating a set of five million potential routes. However, 95 percent of these routes contain zero commuters even after data are 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, of which only 22 percent contain no commuters.

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 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 I allow rents 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 first reduce public-transit travel times for routes that intersect the Phase 2 rail area but that do not intersect Phase 1, and I 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 do three things: 1) to highlight the role of endogenous worker choice, 2) to contrast these effects with those under static worker assumptions, and 3) 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 Figures 8A, 8B, and 8C.

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 percent of

[9] Dingel and Tintelnot (2023) also use LODES data from 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

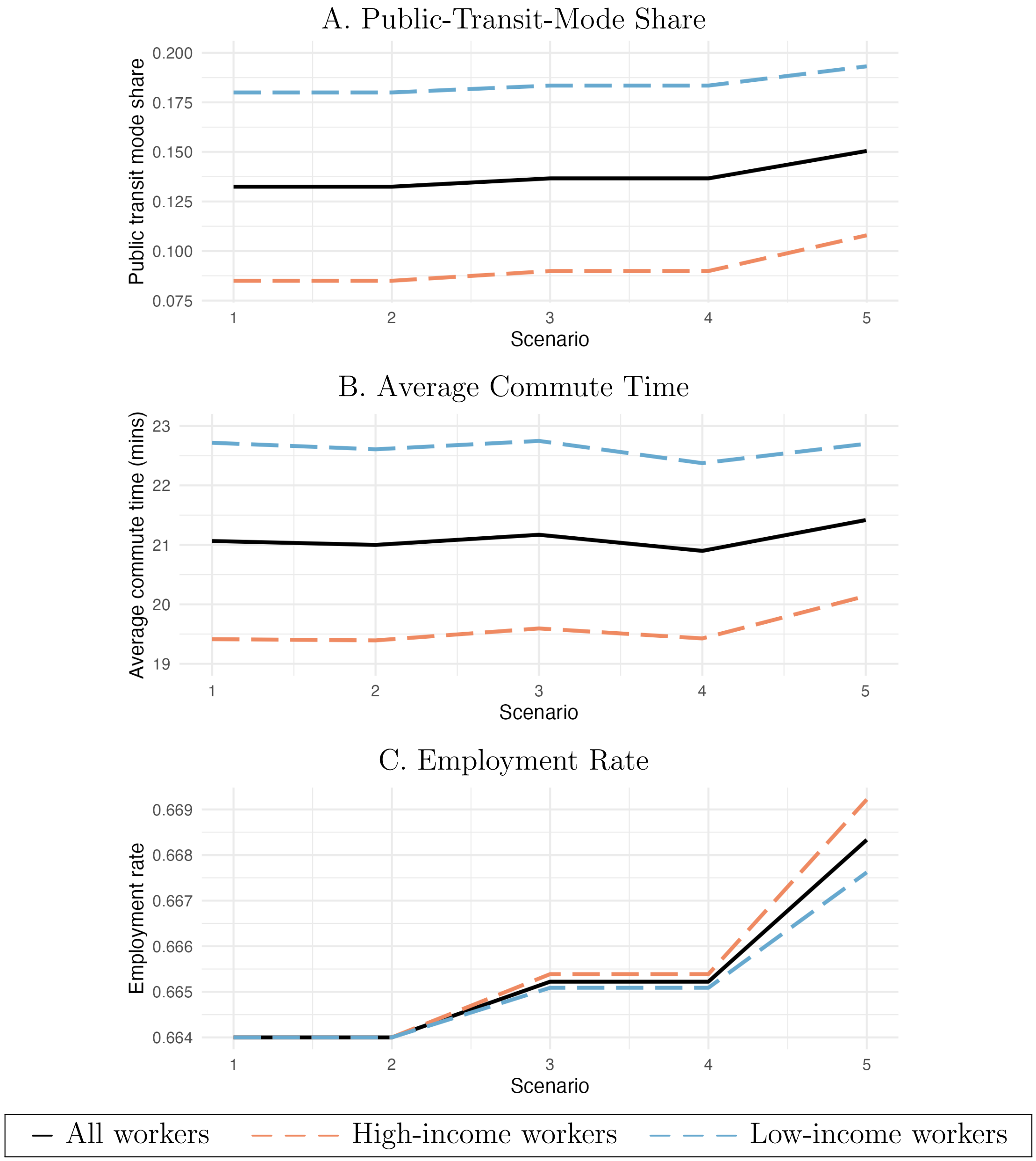
Scenario 1	Pre-rail.
Scenario 2	Phase 1 rail is completed. Worker choices are held constant at Scenario 1 level..
Scenario 3	Phase 1 rail is completed. Endogenous worker choices..
Scenario 4	Phase 2 rail is completed. Worker choices are held constant at Scenario 3 level..
Scenario 5	Phase 2 rail is completed.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

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

low-income workers using transit and 8.5 percent 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 percent for low-income workers and to 9.0 percent 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 percent and 10.8 percent, respectively. Comparing Scenario 1 to Scenario 5, I find that the overall public-transit-mode share rises from 13.2 percent to 15.0 percent—a 14 percent increase. The majority of the improvement (77 percent) 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 average one-way commute time for a low-income worker is 22.7 minutes and that the average for a high-income worker is 19.4 minutes. The changes in commute times are summarized in Figure 8B. The introduction of Phase 1 rail lowers average commute times, as workers who use 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 Oahu, 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 22.6 minutes (a 0.5 percent reduction), while the high-income average commute time remains virtually unchanged (a 0.1 percent reduction). Once endogenous worker

Figure 8: Changes in Aggregate Outcomes



NOTE: 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.

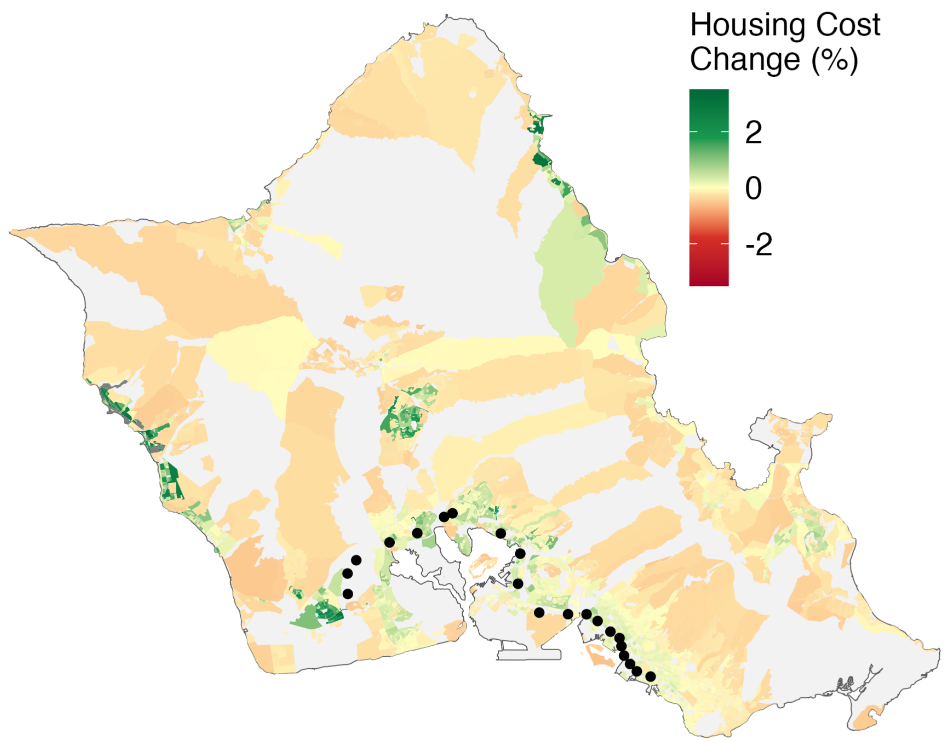
choices are allowed, all of the commuting-time gains are erased. The primary mechanism that causes rail to result in higher commute times is that transit is a slower mode of transportation, even after the improvements attributable to rail. The increase in public-transit-mode share (Figure 8A) translates 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 decisions of low-income workers are sensitive to rents, this causes some low-income workers to leave the rail-serving areas for locations with lower housing costs. Low-housing-cost areas tend to be more peripheral and often include longer commutes. Additionally, lowering commuting costs present 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, 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 aligns more closely with existing high-income commute flows. After I allow for full endogenous sorting (Scenario 5), I find that commute times rise again. In the final equilibrium, I find that the average commute time across all Oahu workers *increases* by 1.7 percent (or 21 seconds) compared to a scenario in which rail was never built. The introduction of transit systems is 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 8C summarizes the effects on the share of workers who are employed. High commuting costs are a disincentive to employment. The provision of rail service allows a worker to access more employment opportunities for a given amount of commuting costs. Depending on workers' 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 percent to 66.8 percent. The effect among low-income workers is a 0.4 point increase, whereas the effect on high-income workers is a 0.5 point increase. According to ACS data for Oahu, aggregate annual income is $43 billion, meaning the induced employment effect could generate roughly $257 million in new annual income on Oahu. 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 Scenarios 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 5.4 percent, while the largest decrease experienced is 0.6 percent. The cost increases near stations are largely offset by rent decreases in neighborhoods far from stations, which become comparatively less desirable.

Figure 9: Estimated Changes in Local Housing Costs



NOTE: 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 gray. Rail stations are shown as black dots.

Some interesting substitution patterns emerge from the model. For example, I find price increases in the Oahu neighborhood of Kailua, located in the northeast part 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 toward 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 that match their preferences. I also observe housing-cost increases on the far west side of Oahu and in the central Oahu 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 Oahu'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 Oahu system is likely to marginally increase the average time spent commuting by a worker on Oahu. However, this is due to the system's success in shifting a meaningful share of the workforce (1.8 percent) 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 Oahu'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 Oahu marginally more likely to move to Oahu, 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 situation in terms of optimizing their location. A complementary policy toward rail service on Oahu 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 I consider this process to be separate from the impacts of rail. Despite these limitations, I believe that this 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 urban-neighborhood-choice modeling 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 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 (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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