Estimating Commuter Benefits of a New Transit System: Evidence from New York City's Ferry Service

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Abstract

This paper estimates the impact of a new transit system on worker outcomes, accounting for endogenous worker decisions. I examine the phased opening of New York City's commuter ferry system. I find evidence of a small but significant shift in commuting flows, towards routes with ferry service, driven by high-income workers. I then propose and estimate a novel structural neighborhood choice model that recovers workers' valuation of ferry service and the aggregate effects of the system on employment. Routes selected for ferry service matched the location preferences of high-income workers, allowing high-income workers to capture almost all direct benefits from the new system. Differing home and work location preferences across income groups largely determine who benefits from a new transit system.

Keywords: Transportation; Transit; Neighborhood choice; Ferry; Structural estimation

JEL: J64; R13; R23; R40; R58

1 Introduction

Understanding the impacts of a new public transit system on workers is complicated by endogenous worker responses. In this paper, I propose an empirical methodology to estimate the impacts of a new transit system in a city with workers who make endogenous labor market and location decisions. I use detailed commuter flow information to estimate the effects of New York City's recent expansion of ferry service on the local labor market.

New York City undertook an ambitious expansion of commuter ferry service starting in 2011, attempting to improve commuter options. I examine whether the ferry had a significant impact on commuter flows within New York City. I find that census tract pairs connected by new ferry routes experienced a significant increase in commuter flows, particularly high-income commuter flows. Using a structural approach, I then recover worker preference parameters for ferry commuting. I innovate on existing structural neighborhood choice methodology by introducing a simple model that accounts for location preferences across worker types and solves for an equilibrium that is consistent with observed commuter flow changes. I argue the proposed model can be simply estimated and requires limited data inputs. Structural model results show both low and high-income workers value ferry service. However, the specific routes selected for ferry service aligned with high-income worker location preferences, which resulted in almost all direct benefits accruing to high-income workers.

This paper fits closely into a growing literature of quantitative spatial equilibrium models. The recent structural modeling approaches are empirical applications of the basic urban spatial model (Alonso, 1964; Muth, 1969; Mills, 1967; Fujita and Ogawa, 1982), and urban choice model (Tiebout, 1956). Anas (1981) and Epple and Sieg (1999) extended the discrete choice framework of McFadden (1973), modeling urban neighborhood choice in a discrete choice framework. Bayer et al. (2004) provided further methodological extensions and Bayer and McMillan (2012) explicitly reconciled neighborhood choice modeling within a Tiebout (1956) framework. Other important applications of neighborhood choice modeling include Sieg et al. (2004); Bayer et al. (2007); Ferreyra (2007), and Ahlfeldt et al. (2015).

Some recent, closely related work has specifically applied quantitative spatial equilibrium models to estimating the benefits of new transit systems. Severen (2023) estimated welfare effects of the Los Angeles subway system using a discrete choice model. The current paper's use of route-level fixed effects applied to panel commute flow data is similar to Severen (2023). Tsivanidis (2023) estimated the impact of Bogota's Bus Rapid Transit system on urban commuting by incorporating multiple worker types and advancing estimation methods. Tyndall (2021) analyzed the effects of US light rail transit systems on commuter flows and neighborhood change, combining a discrete choice framework with parameter estimates generated from an instrumental variable regression analysis. The current paper similarly makes use of reduced-form regression results to parameterize a model and follows some modeling assumptions made in Tyndall (2021). Chernoff and Craig (2022) provided an application for a rail transit expansion in Vancouver, Canada, examining distributional effects across worker types. Mo (2023) modeled household responses to a changing road network in Xiamen, China.

The current paper contributes a further extension to urban discrete choice modeling. I develop a quasi-difference-in-difference setup based on route-level fixed effects. The fixed effects approach constricts the model to closely adhere to observed commute flow data and eliminates the need to directly estimate a bilateral commuting time matrix. Dingel and Tintelnot (2020) provided a methodological review of fixed-effects-based structural estimation strategies, arguing granular datasets with a large number of fixed effects and sparse data coverage can lead to overfitted models with biased results. The approach of this paper, to pool data across 18 years and estimate time-invariant route fixed effects, aims to overcome this issue. Overall, I attempt to synthesize past structural estimation approaches to produce a model that is simple and tractable with limited data requirements.

This paper is particularly concerned with the impact of transit on establishing labor market connections. Kain (1968) introduced the concept of spatial mismatch, arguing that localized unemployment could be driven by insufficient spatial access to job opportunities. Andersson et al. (2018) provided contemporary evidence of spatial mismatch in the US. Some studies have attempted to establish a causal relationship between job access and employment through natural experiments. Holzer et al. (2003) looked at reverse commuters using a new transit line in the San Francisco area. Tyndall (2017) used New York City subway system closures due to Hurricane Sandy as a source of random variation in transit access. Both studies found a positive, causal link between transit access and employment.

The setting of the current paper concerns a commuter ferry system. While buses or trains connect neighborhoods that are arranged linearly, ferry routes may connect neighborhoods that were otherwise spatially isolated from one another. The connecting of formerly disparate neighborhoods through transit provides a cleaner environment to estimate commuter impacts than would be possible for a bus or rail route. Spatially separated neighborhoods are less likely to share underlying, unobserved characteristics or trends, which may contaminate difference-in-difference style designs. Prior literature has responded to spatial endogeneity concerns through instrumental variables (see for example, Chernoff and Craig (2022); Severen (2023); Tyndall (2021)).

Across the US, there are 44 operating commuter ferry services, which provide 90 million passenger trips per year.[1] There is limited economic literature examining the effects of ferry service. Sandell (2017) examined a reconfiguration of Sydney, Australia's ferry system and argued that route selection that accounts for route-level, rather than neighborhood-level, travel demand is important to creating an efficient system. Thompson et al. (2006) discussed the urban form consequences of ferry service in New York City and argued that ferries may play an important role in waterfront Transit Oriented Development (TOD) projects in coastal US cities. Schreurs et al. (2023) provided a detailed description of New York City's ferry expansion and argued that ferry terminal locations were selected based on local real estate development opportunities and that the terminals contributed to local gentrification.

The paper will proceed as follows. Section 2 provides a background of the New York City commuter ferry service. Section 3 describes the data used in the paper. Section 4 presents reduced form estimates of the ferry's impact on bilateral commuter flows. Section 5 presents a structural approach to estimate underlying preference parameters for ferry service and aggregate employment effects of the system and Section 6 concludes.

2 Ferry Service in New York City

Commuter ferry service in New York City has a long history. Before the construction of a bridge and tunnel network connecting Manhattan to Long Island and New Jersey, privately operated ferry services were a vital link in the region. As bridges and tunnels were completed in the late 1800s and early 1900s ferry services were generally phased out.[2] Vilain et al. (2012) provides a useful discussion of the history of ferry services in New York City up to the 2011 opening of the East River Ferry, which is the first expansion route considered in this paper.

This paper will analyze the recent revival of commuter ferry service in New York

[1] American Public Transportation Association 2021 Factbook.

[2] An exception is the Staten Island Ferry, which connects the north of Staten Island with Lower Manhattan and has provided commuter ferry service continuously since 1817. I do not consider the Staten Island Ferry in the analysis, as its impact is constant across the study period.

City, a system now known as NYC Ferry. Figure 1 provides a public map of the six ferry routes operated as of May 2019.[3] The opening dates of the six new ferry routes were staggered from 2011-2018. Figure 2 provides a timeline of route opening dates. The East River route opened in 2011, significantly earlier than the other five routes, which began operating in either 2017 or 2018.[4] I make use of the staggered opening dates as a source of variation in my empirical identification approach.

The New York City ferry system has been the topic of sustained political and public attention. In 2011, under the Bloomberg mayoral administration, the city began operating the East River Ferry route. A comprehensive report on possible ferry system expansion was released in 2011 (NYCEDC, 2011) and updated in 2013 (NYCEDC, 2013). Subsequently, the broader expansion of ferry service became a cornerstone of transit investment efforts under the de Blasio mayoral administration. In 2015 it was announced that the ferry service would be expanded to include an additional five routes with the system being re-branded as NYC Ferry. Investment in the ferry system was justified as a way to relieve stress on the overburdened and aging subway system. An explicit goal of the system was to expand employment opportunities for disadvantaged and isolated workers. For example, at a press conference announcing system expansion, Mayor de Blasio stated; "*If you can't get to a job interview or a job...you just don't have as much opportunity to get ahead economically. We don't want to see that happen.*"[5]

Many local media outlets and transit advocates responded to plans by arguing scarce public transit funds could be more effectively invested in the existing subway and bus systems.[6] Given the locations of planned routes, concerns were raised that ferry service would primarily serve high-income residents of the city and fail to meaningfully improve transit for those most reliant.

The most important ferry node is the Wall Street terminal, which connects to all six ferry routes. The area surrounding the Wall Street station has a high concentration of jobs, particularly high-income jobs. In 2010, 71% of jobs in the Wall Street neighborhood paid more than $40,000 annually, while the rate in the rest of the city was 50%.[7]

[3] I ignore the ferry route to Governors Island, which is not a commuter ferry but provides recreational access to the park on Governors Island.

[4] The Lower East Side route closed in 2020. In 2021, a route serving Staten Island and the west side of Manhattan opened. Both of these events occur after my study period.

[5] Quoted from a July 26, 2017 Press Conference. NYC Mayor's Office. *Mayor de Blasio Makes Announcement About NYC Ferry Service.*

[6] For an example of media coverage see: *A Ferry Subsidy of $24.75 a Ride? New York City's Costs Are Ballooning.* New York Times. April 17, 2019.

[7] I use census tract boundaries to approximate the Wall Street area, which I consider to be all of

Figure 1: Map of Ferry Service

A public map was disseminated by the ferry operator in 2019, showing the routes in operation.

Including the Wall Street station, the system encompasses five stations on Manhattan Island, nine stations in Brooklyn, four stations in Queens, one station in the Bronx, and one station on Roosevelt Island.

Ferry hours and headways vary by route, but ferries generally operate from 7 a.m. to 9 p.m. and run with 20-minute headways on most routes. Ferry fares were set at

Manhattan south of Chambers Street. Wage data is taken from 2010 LEHD LODES Worker Area Characteristics file.

Figure 2: Opening Dates of Ferry Lines

2011	East River.
2017	Astoria. Rockaway. South Brooklyn.
2018	Lower East Side. Soundview.

A timeline of ferry route openings is shown for the six routes operating during the study period.

$2.75, matching subway fares.[8] However, the ferry system utilized a separate payment system and therefore did not allow for free or discounted transfers between the ferry and other modes of public transit. While fares rarely cover the operating costs of public transit systems, the NYC Ferry system required particularly high public subsidies. A nonpartisan audit of ferry operations in 2018 found that every passenger trip required a $10.73 government subsidy. For comparison, subway trips required a $1.05 per ride subsidy, and commuter rail services required a $6 per ride subsidy (Campion, 2019).

In 2018, the annual operating cost of NYC Ferry was reported to be $56.7 million. Capital expenditures to establish the system were estimated to total $639 million. Debt servicing on the bonds needed to fund the capital expenditures was estimated to cost the city $48.6 million per year, for 20 years (Campion, 2019). By adding annual operating expenses to debt servicing I consider the annual public cost of the ferry system to be $105 million.

Despite a significant revival in ferry service, the share of commuters in New York City who commute by ferry is small. According to data from 2016-2020, only 0.3% of New York City commuters used a ferry as their primary mode of commuting. Table 1 provides commuter mode shares. The subway is the most popular mode of commuting in the city, and is the primary mode for 41% of commuters, meaning there are roughly 140 subway commuters for every ferry commuter. Ferry ridership in New York City has experienced growth in recent years. From data spanning 2005-2009 only 0.23% of commuters used a ferry as their primary mode, while the 2016-2020 data shows 0.33%, marking 50% growth. Figure 3 graphs the growth in ferry commuter mode share.

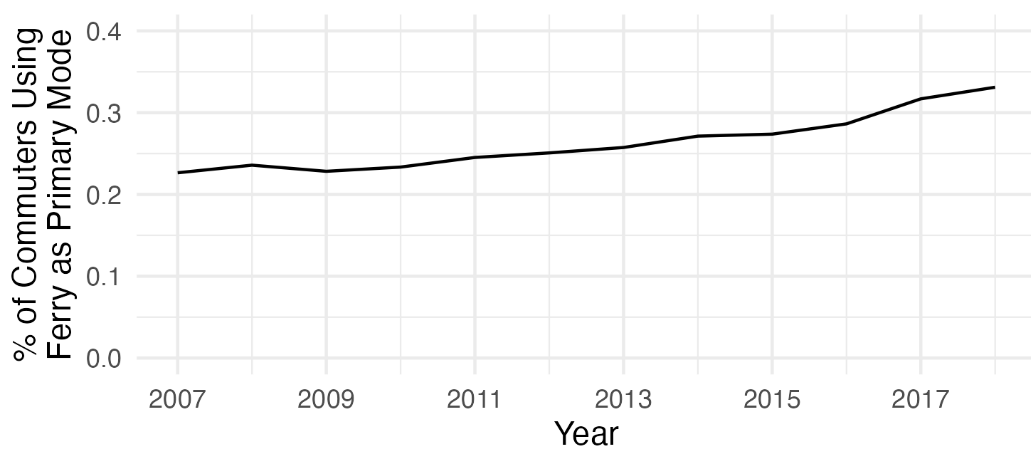
[8] In 2022, standard ferry fares were increased to $4.00, but this change occurred after the study

Table 1: New York City Commuter Mode Shares

	Share of Commuters
Private Vehicle	26.77%
Drove Alone	22.31%
Carpooled	4.46%
Public Transportation	52.82%
Bus	9.76%
Subway	41.24%
Commuter Rail	1.34%
Ferryboat	**0.33%**
Taxicab	1.10%
Motorcycle	0.08%
Bicycle	1.32%
Walked	9.78%
Worked From Home	7.40%
Other Means	0.88%

Data from 2020 5-year American Community Survey.

Figure 3: Ferry Mode Share in New York City



Data is from the 5-year American Community Surveys. Data is plotted according to the center year of the survey. For example, data for the 2018 point includes survey responses from 2016-2020.

The recent expansion of New York City's ferry service is consequential in terms

period of this paper.

of the system's costs as well as the public and political attention the system garnered. Evaluating the labor market consequences of the New York City ferry service is important to understand the impact of this large public investment.

3 Data

I construct a unique data set from multiple sources. Using a full list of 2010 New York City census tracts, I generate a matrix of every possible home-location work-location pair. I then expand this set to include one route-level observation per year across the study period, which covers 2002-2019. New York City contains 2,167 tracts, though a small number of these contain either no housing or no employment across the whole study period meaning they are omitted as possible commute routes. The final set is a balanced panel, containing 82,581,120 route-by-year observations, including 4,587,840 unique routes, 18 unique years, 2,124 unique home tracts, and 2,160 unique work tracts.

To incorporate data on commuter flows, I use the Longitudinal Employer-Household Dynamics, Origin-Destination Employment Statistics (LODES). The data is provided annually as a matrix of bilateral commuter flows at the census block level, recording the number of workers who complete commutes between any two particular blocks. I collapse the data to the census tract level, generating a tract-level matrix of commuter flows for each year from 2002-2019. I join the tract-level LODES matrices onto the full set of all 83 million tract-to-tract by year observations. I add zero values to routes that had no commuters reported in the LODES data. Some routes contain zero reported commuters throughout all years of the study period. I discuss the issue of a large number of zeros in the description of the empirical estimation strategy. To avoid expanding my data set beyond New York City, the analysis ignores any worker in the LODES data who either lives or works outside of the city boundaries.

LODES includes breakouts by worker type. I am specifically interested in differentiating between low and high-income workers. LODES can be grouped into workers earning above or below $40,000 annually. Throughout the paper, I will refer to low-income workers as those earning below $40,000 and high-income workers as those earning above $40,000.

For every route-year observation, I determine whether that route-year is served by a ferry connection. I first geocode ferry terminal locations from a list provided by the City of New York. I generate circular buffers around ferry terminals to identify an area of pedestrian access. In the main specification, I use a 200-meter buffer. I overlay terminal buffers on the census tract shapefile and identify all census tracts that are overlapped by the local buffer of a particular terminal. If the tract and buffer overlap at all I consider the tract to be treated by that ferry terminal. I consult the route map (Figure 1) to identify every pair of terminals that are served by a common ferry route. I use the opening date of each of the six newly established ferry routes. The variable for an active ferry connection takes a value of one if the route is served by a common ferry route, meaning the tracts are both within the buffer of a terminal that accommodates the common route,[9] and the ferry is open to the public in that year.[10]

Figure 4 provides a map of the census tracts that were connected by ferry service by the end of the study period. The majority of connected tracts are located along the East River in Brooklyn and Queens.

Census tracts that are not directly adjacent to a ferry terminal, but still relatively near a terminal, may be partially treated as some workers may choose to walk farther to use the ferry. When conducting analysis I drop nearby tracts to reduce the SUTVA issue of partially treated routes. In the main analysis, I drop routes that include tracts that are not intersected by the 200-meter buffers but are within a 1,000-meter buffer of a terminal. I drop these partially treated routes across the entire study period to maintain a balanced panel. These dropped routes represent only 0.3% of the original sample. I show these tracts in Figure 4.

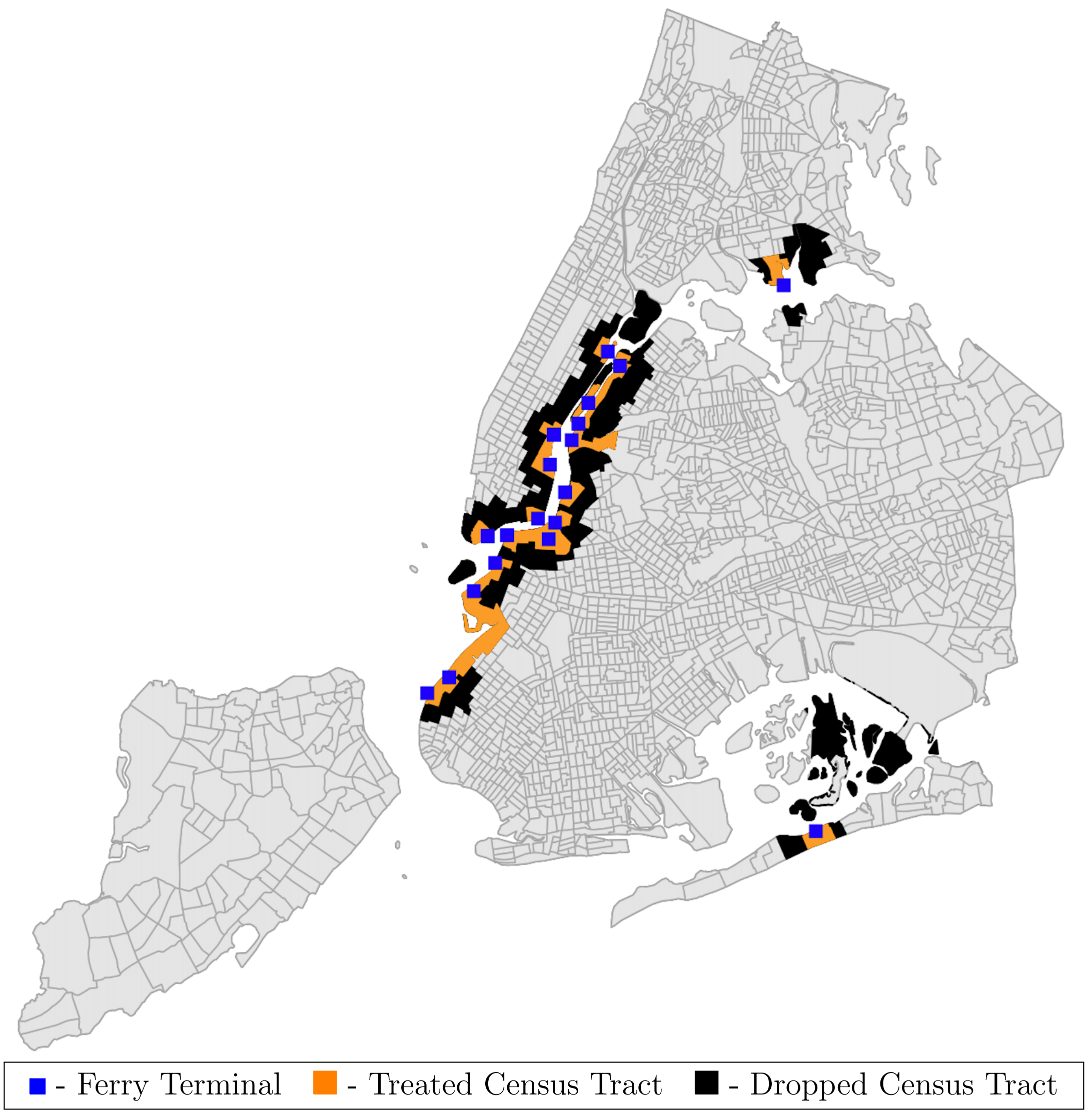
Table 2 provides summary statistics. Across the final sample, the average route has 0.58 commuters, where an average of 0.32 were low-income and 0.25 were high-income. Only a small fraction of routes are connected by the ferry service. Across the whole study period, 0.0035% of routes are connected, which accounts for 2,859 route-year observations. At the end of the study period (2019), I identify 502 connected routes, which comprise 0.011% of that year's routes.

In secondary analysis, I perform census tract-level regressions to test the average effect of a ferry connection on neighborhood conditions. For tract-level analysis, I use the LEHD LODES Resident Area Characteristics and Worker Area Characteristics files.

[9] I ignore the possibility that commuters may transfer across multiple ferry routes. Because of relatively long headways, completing a commute using multiple ferry routes is unlikely to be a reasonable commute in most cases.

[10] Because ferry routes do not necessarily open at the start of a year, and the LODES data is aggregated annually, I consider tracts connected if the ferry connection opened either in a preceding year or at some point during that year. I choose to consider partially treated years as treated rather than untreated in part because anticipation effects among workers mean that labor market responses may precede the actual opening of the ferry connection.

Figure 4: Census Tracts Treated by a Ferry Route



Tracts shown in orange are connected by at least one ferry route. Treated tracts are those that overlap a 200 meter buffer centered on a ferry terminal. Dropped tracts are those that are not overlapped by a 200 meter buffer but are overlapped by a 1,000 meter buffer.

These data files provide more detailed information on commuters but are identified by home and work location respectively, rather assigning workers to specific home-work pairs. Similar to the route level data, I drop tracts that are partially treated (Figure 4).

In the structural estimation section, I will make use of tract-level ACS data, par-

Table 2: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.
Workers	0.577	3.234	0	1166
Low-income workers	0.324	1.677	0	823
High-income workers	0.253	2.051	0	624
Young workers	0.140	0.950	0	590
Middle-aged workers	0.328	1.929	0	571
Older workers	0.108	0.748	0	287
Ferry link dummy	0.000035	0.005894	0	1
N		82,294,092		

Each observation corresponds to a unique route-year combination. Routes are dropped if they include a dropped tract as identified in Figure 4. The data set is a balanced panel of 4,571,894 routes and 18 years.

ticularly median rents. I take data from the mid-point of the study period by using the 2013 5-year ACS.

4 Estimating the Commuter Flow Impact

In this section, I estimate the growth in route-level commuter flows caused by a ferry connection. When two tracts become connected by the ferry, the commuting cost between those tracts is reduced and this may attract new commuters. Workers may shift towards the ferry-connected routes by changing their home location, their work location, or entering the labor force. Workers may substitute away from an existing or prospective job. I explore the mechanisms of neighborhood sorting, extensive-margin employment decisions, and aggregate employment effects more completely in the subsequent structural estimation section. Accurately estimating the partial effect of a ferry connection on the number of commuters completing that route provides a test for whether the ferry service meaningfully affected commute flows and will be an important parameter in the structural estimation methodology.

4.1 Regression Methodology

I estimate new labor market connections through a difference-in-difference setup. The main regression specification is shown in Equation 1. C_{rt} is the number of commuters who commute along route r in year t. F_{rt} is a dummy variable that takes a value of one if route r was connected by the ferry system in year t. Φ_r is a vector of route fixed effects and Ψ_t is a vector of year fixed effects.

$$C_{rt} = \beta_0 + \beta_1 F_{rt} + \Phi_r + \Psi_t + \varepsilon_{rt} \tag{1}$$

The inclusion of route fixed effects absorbs any average difference in commute popularity across routes. Year fixed effects absorb any city-wide changes in commuter flows over time. Identification of the effect of the ferry connection makes use of only the temporal changes in flows that correspond to the timing of ferry route openings. The coefficient of interest is β_1, which captures the partial effect of a ferry connection on the number of commuters using that route, relative to non-treated routes. In some specifications, rather than capture the total number of workers, C_{rt} will capture the number of workers of a specific type, for example, low-income workers.

I assume a parallel trend assumption where the growth in commuting flows along treated and control routes would have proceeded similarly if not for the introduction of the ferry system. While some commuting infrastructure changed during the study period, for example, the Second Ave Subway extension[11] (Gupta et al., 2022) and the introduction of some express bus routes (Tyndall, 2018), I assume the impacts are spatially orthogonal to the impact of ferry routes.

Recent developments in difference-in-difference methodology have yielded improved estimators for cases with staggered treatment (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021), which is the case here. The issues raised in the literature apply particularly to the current scenario because the effect of treatment by a ferry connection may trigger a shift in commuter *growth* over time, rather than a discrete level change. As outlined in Goodman-Bacon (2021) the staggered timing of treatments would result in a biased estimate when using a conventional two-way fixed-effect estimator. I use the estimation strategy for staggered treatment in difference-in-difference settings outlined in Callaway and Sant'Anna (2021), which is not subject to the bias identified in Goodman-Bacon (2021).[12]

In addition to estimating the effect of a ferry connection on route-level commuter

[11] I drop a set of tracts from analysis that are more than 200 meters but less than 1,000 meters from a ferry terminal (Figure 4). Coincidentally, the eight census tracts that are directly bisected by the Second Ave Subway expansion are all within the 200 meter to 1,000 meter range and are dropped from analysis. Therefore, the direct effect of the subway expansion on worker flows to or from tracts adjacent to the new subway stations will not affect the analysis. Spillover effects of the subway expansion to other tracts could effect results. I assume these effects are orthogonal to the effect of the ferry system.

[12] In Appendix A, I provide alternative results using a standard two-way fixed effect (TWFE) approach (Table A1). I am also able to provide a TWFE specification that includes location specific linear time-trends (Table A2). I find similar results across all specifications.

flows, I estimate the effect of being connected to the ferry network on a census tract's number of locally residing workers and the number of local jobs. Equation 2 provides the regression equation for this tract-level analysis.

$$Y_{jt} = \alpha_0 + \alpha_1 F_{jt} + \Phi_j + \Psi_t + \varepsilon_{jt} \tag{2}$$

Y_{jt} is the number of workers or jobs located in tract j in year t, depending on what is being tested. F_{jt} is a dummy variable that takes a value of one if that tract is treated by an active ferry terminal in that year, meaning there is an open ferry terminal in the tract or within 200 meters of its boundary. Φ_j is a vector of tract fixed effects, and Ψ_t is a vector of year fixed effects. The coefficient of interest is α_1, which captures the partial effect of a local ferry terminal on the number of locally residing workers or jobs. I estimate Equation 2 using the Callaway and Sant'Anna (2021) method.

4.2 Regression Results

Table 3, column 1 provides the main regression results (Equation 1). I find that when two tracts were directly connected through the ferry system the number of workers commuting between those tracts increased significantly, by 2.4 workers, on average. Among 502 treated routes, the average commuter flow in the pretreatment period was 6.2, meaning the ferry connection increased commute flows along these routes by 39%. For comparison, Severen (2023) found that tracts connected by LA's metro system experienced a 10-22% increase in commuting. As noted, subway or bus lines connect areas that are linearly arranged and were therefore relatively accessible to one another to begin with. Ferry connections link neighborhoods that were previously more isolated from one another and may therefore represent a more significant reduction in commute cost between tract pairs.

The estimate is affected by a possible SUTVA violation. If the workers moving to the ferry connected route were drawn from a control route, they contribute to the effect by both increasing the treatment route flows and decreasing the control route flows. This effect would bias the estimates upwards. The β_1 estimate is effectively an upper-bound on the job creation impact of the ferry system. While some of these new flows could be from previously unemployed workers, a portion may be workers who would otherwise have been employed along a different commuting route. I account for the effect of flows shifting between the treated and control units in the subsequent structural model.

Table 3: Effect of Ferry Connection on Commuter Flow

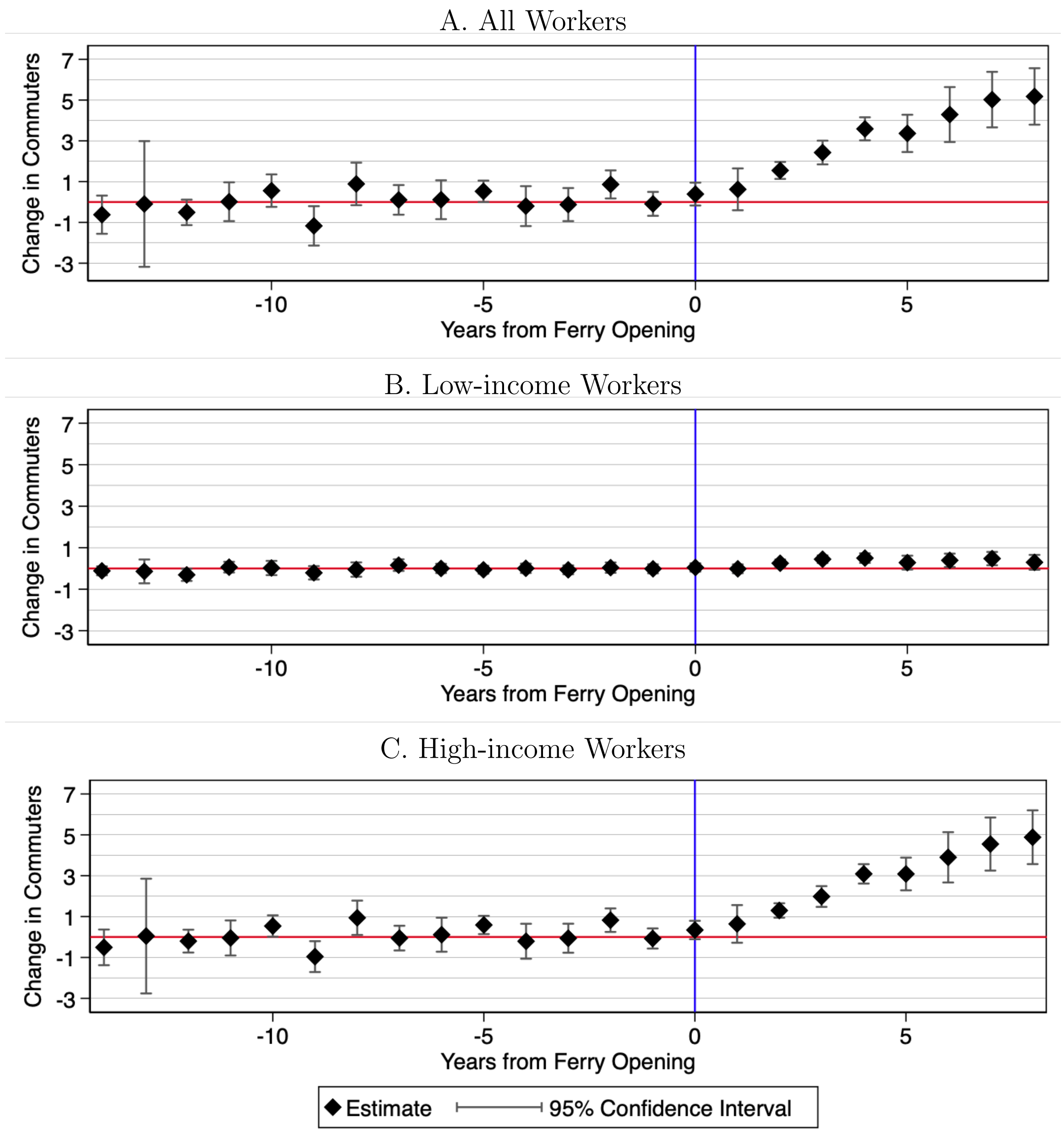
	All Workers	Low-income	High-income
	(1)	(2)	(3)
Ferry link dummy	2.408**	0.243*	2.165**
	(0.392)	(0.096)	(0.364)
Year fixed effects	Y	Y	Y
Home-work pair fixed effects	Y	Y	Y
N	82,294,092	82,294,092	82,294,092
Pre-treatment average	6.181	1.656	4.525
% change	+39.0%	+14.7%	+47.8%

Significance levels: $*$: 5% $**$: 1%. The estimation approach follows Callaway and Sant'Anna (2021). Standard errors are shown in parenthesis.

Table 3 provides results separately for low-income (column 2) and high-income workers (column 3). The workforce in New York City is roughly evenly split between low and high-income workers, with 44% of workers being in the high-income group. However, among commute routes that would gain a ferry connection, the pre-ferry flows were 73% high-income workers, demonstrating that high-income workers were disproportionately common along the routes selected for ferry service, even before service began. In addition to high-income workers already having commute routes that were more likely to benefit from ferry service, I find more high-income workers altered their commutes to take advantage of ferry service. I find a ferry connection increased the average number of low-income workers on a route by 0.24, but increased the number of high-income workers by 2.17. Therefore, high-income workers represent 90% of induced commuter flows. The over-representation of high-income commuters in pre-ferry flows and their over-representation in induced commuter flows are consistent with public concern that the ferry system would disproportionately serve high-income groups.

Figure 5 visualizes the main result as an event study, shifting the staggered treatment years so that 0 indicates the first year ferry service was available for a route. I again adopt the methods described in Callaway and Sant'Anna (2021) to construct the event study estimates. Panel A provides results for all workers, while Panels B and C provide results for low and high-income workers respectively. Before treatment with ferry service, I find no evidence of a sustained difference in trends between the treated and control routes, which provides evidence for the validity of the parallel trend assumption. After treatment, I find a statistically significant effect beginning two years after the ferry opening. I find evidence of a change in the growth of commuters that is specific to ferry-treated routes, as opposed to an immediate level shift. The effect appears to stabilize in the final years observed, with an average increase of about five commuters per connected tract pair.

Figure 5: Event Study of Ferry Treatment Effect on Route Level Flows



Estimates and confidence intervals are calculated using the methods described in Callaway and Sant'Anna (2021).

By 2019, the ferry system connected 502 tract pairs. The final point estimate in

Figure 5A equals 5.178, which I take to be the long-run effect of a connection. The estimate suggests that routes with ferry service gained 2,600 workers, relative to routes untreated by a ferry connection. The impact of ferry service on the overall city labor force was small; 2,600 workers represent only 0.1% of New York City's total labor force. Additional commuters may have benefited from ferry service by switching modes, for example from subway to ferry, but not switching their origin-destination pair on account of ferry service.

Figure 5 Panels B and C show that the effect of a ferry connection on worker flows is almost entirely among high-income workers. While I estimate a significantly positive effect for low-income workers in some years, the magnitude is negligible. By the final period of the event study the effect of low-income flows is not statistically significant.

As a control group, I make use of all route-by-year observations that were not treated by a ferry. While using the full sample makes use of all statistical variation available, the use of such a broad control group may include observations that are very different from the set of waterfront tract pairs that are treated. Plausibly, the ferry-treated routes could be subject to a different set of non-ferry-related shocks over the study period, which could bias estimation. As a robustness check, I provide two alternative sets of results based on a limited set of control routes. First, I limit the routes to only those where the home tract is waterfront, this reduces the sample by 87%. Second, I provide results where the sample of routes is limited to only those where the home tract received a ferry terminal by the end of the study period. This method essentially compares ferry-treated routes, to routes where the home neighborhood is treated by a ferry, but a ferry does not provide access to the work destination. The second limitation reduces the original sample by 98.6%. I provide results in Appendix A. The alternative estimates range from 2.3-2.5, which are almost identical to the full sample specification (Table 3). While the full set of routes is large, the meaningful treatment variation is confined to a small number of routes. The high-level fixed effects mean the inclusion of irrelevant control routes does not significantly affect results.

Table 4 breaks out results by the age of workers. LODES divides workers into those under 30 years of age, those 30-54, and those 55 or older. I refer to these groups as young, middle-aged, and older in analysis. I find that middle-aged workers are most responsive to the introduction of ferry service. Relative to pre-ferry levels, a ferry connection increased the flow of young workers by 18%, the flow of middle-aged workers by 52%, and the flow of older workers by 31%. In addition to appealing to higher-income workers, the ferry service also seemed to appeal disproportionately to middle-aged workers.

Table 4: Effect of Ferry Connection on Commuter Flow, By Age

	Young (1)	Middle-aged (2)	Older (3)
Ferry link dummy	0.302*	1.795**	0.310**
	(0.134)	(0.290)	(0.076)
Year fixed effects	Y	Y	Y
Home-work pair fixed effects	Y	Y	Y
N	82,294,092	82,294,092	82,294,092
Pre-treatment average	1.708	3.466	1.007
% change	+17.7%	+51.8%	+30.8%

Significance levels: $*$: 5% $**$: 1%. The estimation approach follows Callaway and Sant'Anna (2021). Standard errors are shown in parenthesis.

In addition to testing for the effect of a ferry connection on route-level flows, I also test for induced changes in a tract's worker population using the tract level worker counts described in the previous section (Equation 2). Table 5 estimates the partial effect of gaining ferry service on the number of workers living in those tracts, broken out by worker characteristics. I find a large increase in the total number of workers living within ferry-treated tracts. Gaining ferry service is correlated with an increase of 408 local workers. The overall increase in workers suggests that the ferry system was accompanied by an expansion in local housing supply. Schreurs et al. (2023) provides discussion of how ferry terminals were often accompanied by property development, particularly the creation of new condominium units close to terminals. A shift of original local workers into the labor force could also explain some of the rise in workers.

The importance of Wall Street as a node of the ferry system may appeal disproportionately to workers in finance or professional services, industries that are concentrated in the Wall Street area. Additionally, many of the residential areas served by ferries had high home prices, which may also limit the ability of workers in lower-income industries from moving to benefit from ferry service. While I do not have detailed industry breakouts of commuter flows, I do have industry details for tract-level workforce counts. I test whether a ferry terminal changed the industry composition of the locally residing labor force (Table 5).

For the average treated tract, among the 408 new local workers, 373 (91%) were high-income workers. I find significant increases in workers employed in FIRE industries (Finance, Insurance, and Real Estate) and Professional Services, with an increase in local workers of 29% and 39% respectively. Overall, 43% of the worker population growth can be attributed to these industries. Contrastingly, workers employed in lower-skilled, lower-paid industries such as Health Services and Accommodation and Food Services saw small, only marginally significant increases of 6% and 15%. The workforce growth effects are consistent with the ferry terminals attracting primarily high-income workers employed in high-wage industries such as finance.

Table 5: Effect of Ferry Connection on Local Worker Population

	All Workers (1)	Low-income (2)	High-income (3)	F.I.R.E.† (4)	Professional Services (5)	Health Services (6)	Accom./ Food (7)
Ferry terminal dummy	407.818**	34.946	372.872**	85.903**	90.976**	13.699	18.680*
	(118.121)	(25.483)	(97.206)	(22.222)	(22.706)	(17.524)	(7.602)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y
Tract fixed effects	Y	Y	Y	Y	Y	Y	Y
N	38,232	38,232	38,232	38,232	38,232	38,232	38,232
Pre-treatment average	1800.557	709.445	1091.112	298.504	233.995	243.693	121.936
% change	+22.6%	+4.9%	+34.2%	+28.8%	+38.9%	+5.6%	+15.3%

Significance levels: $*$: 5% $**$: 1%. The estimation approach follows Callaway and Sant'Anna (2021). Standard errors are shown in parenthesis. †Finance, Insurance, and Real Estate.

In Table 6 I conduct the same exercise for the number of jobs located within the ferry-treated tracts. I do not identify statistically significant changes in the number of jobs sited in ferry-treated tracts after the ferry system opens. The point estimate for the total number of jobs indicates ferry treatment increased the number of local jobs by 24%, but the effect is not statistically significant. I do find a statistically significant increase in Accommodation and Food Service jobs in treated tracts. The foot traffic generated near ferry terminals could spur the creation or expansion of restaurants and cafes to cater to commuters, explaining the effect. Additionally, the ferry system itself employed workers in this industry.

Table 6: Effect of Ferry Connection on Local Job Counts

	All Workers (1)	Low-income (2)	High-income (3)	F.I.R.E.† (4)	Professional Services (5)	Health Services (6)	Accom./ Food (7)
Ferry terminal dummy	1160.881	485.342	675.539	-385.035	306.032	297.391	130.584**
	(890.968)	(317.431)	(599.869)	(583.690)	(167.160)	(434.942)	(43.132)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y
Tract fixed effects	Y	Y	Y	Y	Y	Y	Y
N	38,880	38,880	38,880	38,880	38,880	38,880	38,880
Pre-treatment average	4762.076	2183.152	2578.924	1447.363	469.487	709.297	131.248
% change	+24.4%	+22.2%	+26.2%	-26.6%	+65.2%	+41.9%	+99.5%

Significance levels: $*$: 5% $**$: 1%. The estimation approach follows Callaway and Sant'Anna (2021). Standard errors are shown in parenthesis. †Finance, Insurance, and Real Estate.

5 Structural Estimation of Worker Response

I aim to provide a concise structural estimation strategy. The method can be applied to new public transit infrastructure that affects a subset of the commute routes within a larger city or region, where commuting flow data is available for both the period before and after the infrastructure began operating.

The above analysis establishes that the introduction of the ferry service had a measurable impact on commuter flows in New York City. However, the reorientation of commuter flows could have come from several distinct mechanisms. Workers have some power to select the location of their home,[13] the location of their workplace, and whether they are employed at all. The opening of the ferry could have impacted none or all of these decisions for a particular worker. On the firm side, firms may be more likely to expand employment at locations connected by the ferry route as it reduces commuting costs for some prospective workers. Because the data does not capture longitudinal variation in the behavior of individual workers or firms, I rely on a structural estimation approach that models rational worker and firm behavior and maps changes to the commuting network onto the observed changes in commuter flows.

Understanding the mechanisms generating the change in commute flows has important policy implications. The introduction of a new transit system reduces the costs of some commutes, which may help unemployed workers attain employment, as predicted by the spatial job search and spatial mismatch literatures. Also consistent with the regression results would be that the observed changes in commuter flows are entirely explained by worker and firm location sorting with no new employment created. Tyndall (2021) demonstrated that new transit infrastructure can actually lower aggregate employment in a city where workers have heterogeneous location preferences. If employed workers with a high labor supply elasticity are crowded out of accessible areas by employed workers with low labor supply elasticity the equilibrium number of employed workers can decline. This could occur if the transit amenity pushes up local housing costs in central areas, causing central-city gentrification and low-skill worker displacement. Given that the expansion of labor market opportunity, particularly for low-skilled or low-income workers, is a common goal of transit investment, it is important to understand how to design transit systems to maximize the labor market benefits.

[13] For example, Glaeser et al. (2008) demonstrated workers who value transit may move towards transit.

Below, I outline a quantitative spatial equilibrium model. By pooling data across multiple years I provide time-invariant estimates of route preference for low and high-income workers that allow the model to match average flow data. The route preference parameters are analogous to route-by-worker-type fixed effects. I then apply the time-variant, ferry-induced commuter flow changes estimated in the preceding section. I recover ferry preference parameters that precisely predict the shift in commuter flows towards ferry-treated routes. Knowing these parameters and the distribution of workers across routes, I can estimate aggregate effects and a distribution of direct benefits.

5.1 Structural Model Setup

I propose a static model of worker choice that will take the following general form. The utility of a worker is represented by a Cobb-Douglas style function represented by equation 3.

$$U_{ijk} = (C + \rho_{s(i)F(jk)})^{\gamma_{s(i)}} H^{(1-\gamma_{s(i)})} \chi_{s(i)jk} + \xi_{ijk} \tag{3}$$

Workers derive utility from numeraire consumption (C) and the consumption of generic units of housing (H). The share of income a worker spends on housing is set by $1 - \gamma_{s(i)}$. i indexes the worker, j indexes the home tract, k indexes the work tract, $s(i)$ indexes the income level of worker i, and $F(jk)$ indexes whether tracts j and k are connected by a ferry.

$\rho_{s(i)F(jk)}$ takes a value of zero if tracts j and k are not connected by a ferry route ($F(jk) = 0$). If tracts j and k are connected ($F(jk) = \mathbb{1}$), $\rho_{s(i)\mathbb{1}}$ is the consumption premium associated with the benefits of a ferry connection. $\rho_{s(i)\mathbb{1}}$ will be endogenously determined. Because $\rho_{s(i)F(jk)}$ enters additively with numeraire consumption (C) it will be interpretable as the worker's valuation of ferry service, expressed in dollars. Workers can be high-income ($s(i) = h$) or low-income ($s(i) = l$) and this characteristic is fixed. $\chi_{s(i)jk}$ is a route-by-worker-type specific idiosyncratic preference parameter. Some routes may provide higher utility than others based on their unique characteristics such as commuting time, traffic conditions, commuting mode options, housing and job prospects at the origin and destination tract, or any other route-specific, but time-invariant, characteristics. All workers of the same income type (low or high) share a common evaluation over routes ($\chi_{s(i)jk}$) and this preference vector is time-invariant. Additionally, ξ_{ijk} follows a Type 1 extreme value distribution and captures a worker's individual idiosyncratic preferences over each commuting route.

Each worker operates under a budget constraint (Equation 4). $w_{s(i)k}$ represents the wages paid to worker i. Employed workers earn a set wage dependent only on their type. I allow for non-employed workers by including a null element of work location choice ($k = \emptyset$). When a worker makes this selection they receive a reduced, but strictly positive, public assistance wage ($w_{i\emptyset} = w^P$). The variable p_j represents the price for a generic unit of housing in tract j. Workers choose housing quantity (H) consistent with utility maximization. All workers are renters and pay rent to a landlord outside of the local economy.

$$w_{s(i)k} = Hp_j + C \tag{4}$$

I combine the utility function and budget constraint to generate an indirect utility function (Equation 5).

$$\begin{aligned} V_{ijk} &= (w_{s(i)k} + \rho_{s(i)F(jk)})\gamma_{s(i)}{}^{\gamma_{s(i)}}(\frac{1-\gamma_{s(i)}}{p_j})^{1-\gamma_{s(i)}}\chi_{s(i)jk} + \xi_{ijk} \\ V_{ijk} &\equiv v_{ijk} + \xi_{ijk} \end{aligned} \tag{5}$$

The extreme value distributed idiosyncratic error term produces a multinomial logit probability function (Equation 6), capturing the probability a worker selects a specific home-work pair (P_{ijk}). The upper bar notation indicates the maximum value in the set.

$$P_{ijk} = \frac{e^{v_{ijk}}}{\sum_1^{\bar{j}} \sum_1^{\bar{k}} e^{v_{ijk}}} \tag{6}$$

I model firms such that each tract contains a single representative profit-maximizing firm. Each firm (tract) has a production technology that takes low-income labor, high-income labor, and capital as inputs. Firms exist in a competitive market, possess constant returns to scale production technology, have access to a perfectly elastic external capital market, and earn zero profits. In such an environment, firms will expand to hire as many workers as are willing to accept employment at a persistent wage level. Therefore, high and low-income worker wages are fixed in the model. Similarly, firm wage offers do not vary across space. Any qualitative differences across firms are subsumed by the route level preference parameters. One reason low (high) income workers may prefer working at a particular location is the job characteristics of that local firm, but this effect is not uniquely identified relative to any other attractive quality of that route.

I describe a static model. When estimating the impacts of the ferry system I reestimate the model under different ferry configurations to recover how expansions of the ferry system impact the distribution of worker route choices.

5.2 Structural Model Solution Method

To solve the model I impose seven exogenous structural parameters (Table 7). The annual wages for low and high-income workers are set to \$18,000 and \$69,000 respectively. I recover these estimates from the 2013 5-year ACS data, which provides average earnings for workers earning above and below the \$40,000 income group cut-off as defined in the LODES data. I set non-employment assistance income (w^P) equal to half the low-income level. I parameterize the share of income spent on housing (γ) with 2013 5-year ACS microdata from IPUMS. The median worker earning above \$40,000 spends 17% of their income on either rent or mortgage payments. Among those earning below \$40,000, microdata indicates the median worker spends 54% of their income on housing, reflecting the expensive housing market of New York City and the low cutoff used to define the low-income population. I therefore set $\gamma_{s(i)=l} = 0.46$ and $\gamma_{s(i)=h} = 0.83$.

Table 7: Exogenous Model Parameters

Symbol	Value	Description
$w_{s(i)=l}$	18	Annual income for low-income workers (\$1,000s)
$w_{s(i)=h}$	69	Annual income for high-income workers (\$1,000s)
w^P	9	Annual public assistance income for non-employed workers (\$1,000s)
$\gamma_{s(i)=l}$	0.46	Share of income spent on non-housing consumption for low-income workers
$\gamma_{s(i)=h}$	0.83	Share of income spent on non-housing consumption for high-income workers
$F_{s(i)=l}$	0.296	Ferry treatment effect on low-income commuter flow
$F_{s(i)=h}$	4.882	Ferry treatment effect on high-income commuter flow

I impose seven parameters on the model. Income and housing expenditure estimates are taken from the 2013 5-year ACS.

When ferry connections are introduced, I limit the model's solution space to match the estimated changes in commuter flows identified for low and high-income workers in Section 4.2. I found that a ferry connection increased the average number of low and high-income workers commuting on a route by 0.296 and 4.882 respectively (Figure 5).[14]

[14] I assume the final estimate of the event study represents the long-run effect of a ferry connection. As an alternative method, I estimate the model using the difference-in-difference point estimates from Table 3, which were 0.243 and 2.165. Adopting these values generally lowers the model estimates. For example, I find the ferry consumption premiums are 15% lower for low-income workers and 52% lower for high-income workers. The estimates for new employment gained among high income workers are

The model solution generates these shifts by identifying the values workers place on a ferry connection ($\rho_{l\mathbb{1}}$, $\rho_{h\mathbb{1}}$) that generate worker flow shifts equal to those estimated in the regression analysis.

In addition to the exogenous parameters shown in Table 7. I impose tract-level rents from the 2013 5-year ACS. For the tracts where rent data is not available, I impute the average city-wide rent ($14,400 annually). When a worker selects to live in tract j they pay the median market rent for that tract (p_j), multiplied by their housing quantity choice H. In the pre-ferry period, tract rents match ACS estimates. However, rents are allowed to endogenously adjust to clear the housing market of each tract once ferry service is introduced. The initial rent levels do not have a first-order importance because variation is subsumed by the route level preference parameters ($\chi_{s(i)jk}$) in estimation.

To allow for workers who are not employed, I add one route choice for every populated tract, where the work location is null. I use 2011 ACS data for the share of the over-16 population in each tract that is not in the labor force. I assign every tract a population of low and high-income workers who are not employed to match the overall rate in the ACS data. While the LODES data supplies the number of employed workers completing each route, I add in additional workers for the non-employed.

For the 2002-2019 study period, the level of ferry service can be effectively divided into four periods (Figure 2). The pre-system period spans 2002-2010. The second period (2011-2016) includes only ferry service for the East River route. The third period (2017) adds service for the Rockaway, South Brooklyn, and Astoria routes. The fourth period (2018-2019) includes service for all six routes.

I proceed to solve the model in two steps. First, I estimate the vector of route-by-worker-type consumption premiums, $\chi_{s(i)jk}$. I collapse the 18 years of data to the route-by-worker-type level, taking the average values of bilateral commuter flows across all years. I set rents and wages according to the exogenous values. I then use contraction mapping to recover the unique vector $\chi_{s(i)jk}$ that generates the observed, average bilateral commuter flows. In solving for the equilibrium, elements of $\chi_{s(i)jk}$ are raised or lowered to precisely match the averaged commute flow data.

By pooling the data I avoid relying on an overly sparse matrix. Using the same LODES data from New York City, Dingel and Tintelnot (2020) argued that a single year of data produced severe bias from overfitting while pooling three years of data

reduced by two-thirds, and the low-income workers employment effect becomes approximately zero.

significantly reduced the issue. In the method proposed in this paper, I pool 18 years of data, which significantly reduces the sparseness of the matrix and reduces concerns about overfitting the data. A primary concern in Dingel and Tintelnot (2020) is that out-of-sample counterfactual estimates will be biased by the significant amount of idiosyncratic behavior captured in the granular data. In this exercise, I do not estimate a purely hypothetical scenario, rather I constrain the model to generate commuter flow changes that were produced by an event with observable effects.

Of 9.2 million possible routes and worker types in the cross-sectional matrix, 53% have zero commuters recorded for every year of the LODES data. In effect, the model assigns a χ_{jk} for these routes equal to negative infinity. It is computationally equivalent to drop these routes from the analysis. I observe the post-treatment period and therefore know that, even after ferry service was available, these routes still attracted no commuters, suggesting these routes are unlikely to correspond to viable routes even in the counterfactual environment.

In solving $\chi_{s(i)jk}$, I produce two vectors of route-level preference parameters, one for each worker-type. Tract pairs that provide easy commutes will be more popular (conditional on differences in rents in the home tract) and therefore require a higher value of $\chi_{s(i)jk}$ to match the data. Estimating $\chi_{s(i)jk}$ averaged over the entire study period allows for the vector to be interpreted as the time-invariant component of common route preferences.

Moving to the second step of the estimation method, I hold constant the route-level consumption premiums ($\chi_{s(i)jk}$) that were generated in the first step and expand the data to include the four distinct periods of ferry service. Holding route preferences ($\chi_{s(i)jk}$) constant, I limit the model to generate the route-level ferry treatment effects calculated in the regression analysis (F^l and F^h). I allow the worker-type specific consumption premiums for ferry service ($\rho_{s(i)=l,F(jk)=\mathbb{1}}$, $\rho_{s(i)=h,F(jk)=\mathbb{1}}$) to adjust to generate the correct change in commuter flow. For example, $\rho_{h\mathbb{1}}$ will adjust so that a ferry connection induces an average of 4.882 additional high-income workers to select a ferry-serviced route relative to the average change in workers selecting non-ferry-serviced routes. I allow the vectors of period-specific rents to adjust to clear the housing market by attracting the correct number of residents to each tract, though a tract's mix of low and high-income workers may change.

Positive ferry amenity values (F^l and F^h) will push up demand to live in tracts that are connected by a ferry route. The increase in demand, and constant housing supply, results in an increase in rents. The increase in rents affects both low and high-income workers as they compete in a common housing market.

I define the model solution of the second step as a vector of rents and ferry preference parameters where each worker chooses the commuting route that maximizes their utility, the housing market clears, and the shifts in commuting flows towards ferry routes match the observed values (F^l and F^h). The conditions represent a Nash equilibrium for all workers.

The utility function of workers does not consider the characteristics (low or high-income) of other workers in their neighborhood. Therefore, the decisions of workers do not affect the utility of others except through housing rents. Bayer and Timmins (2005) as well as Allen et al. (2020) provide a detailed proof of solution uniqueness for this class of spatial sorting models, which applies to the current model.

5.3 Structural Model Results

The main parameters of interest for the structural estimation model are the consumption premiums associated with route ferry access for both low and high-income workers ($\rho_{s(i)=l,F(jk)=\mathbb{1}}$, $\rho_{s(i)=h,F(jk)=\mathbb{1}}$). $\rho_{s(i)F(jk)}$ takes a value of zero for tract pairs (jk) that are not connected by a ferry, by construction. In the equilibrium solution, for tract pairs connected by a ferry route, $\rho_{s(i)\mathbb{1}}$ takes a value of 0.767 for low-income workers and 1.068 for high-income workers (Table 8). The values can be interpreted in the model as consumption premiums represented in \$1,000s, meaning low and high-income workers value a ferry connection as being equal to \$767 and \$1,068 of annual consumption respectively (Table 8). As demonstrated in the regression analysis, it is primarily high-income workers who adjust their behavior to make use of the ferry. However, I find both low and high-income workers place a similar, positive value on a ferry connection.

Table 8: Structural Model Solution Parameters

Symbol	Value	Description
$\rho_{l\mathbb{1}}$	0.767	Ferry connection consumption premium (\$1,000), low-income workers
$\rho_{h\mathbb{1}}$	1.068	Ferry connection consumption premium (\$1,000), high-income workers

Solving the model yields the consumption premium parameters.

Wages for high-income workers in the model are 3.8 times that of low-income workers. As a fraction of income, low-income workers value a ferry connection at 4.3% of income, while high-income workers value the connection at 1.5% of income. If low and high-income workers took the ferry at similar rates, the benefits relative to income of the ferry would primarily flow to low-income workers. However, for reasons discussed below, high-income workers are much more likely to benefit directly from the ferry.

In equilibrium, the provision of a local ferry connection increases local rents for treated tracts, as it represents a local amenity. The results of the structural model suggest a ferry terminal causes an average rent increase of \$101.93 (\$8.41 per month) or a 0.51% increase relative to the average pre-ferry rent in treated tracts. The increase in rent makes the tract less desirable, ceteris-paribus, repelling enough residents so the local housing market clears.[15]

The regression analysis suggested that few low-income workers are incentivized to switch to a commuting route with a ferry (Table 3). If low-income workers placed no value on a ferry connection ($\rho_{l\mathbb{1}} = 0$) they would still be exposed to the rent increases around ferry terminals brought on by the behavior of high-income workers. If low-income workers did not value the ferry at all, we would expect a decline in the number of low-income workers commuting along ferry routes, as they are repelled from living in ferry terminal areas as local rents increase. The positive valuation of ferry service estimated for low-income workers (\$767 annually) more than offsets the repellent effect of higher rents, leading to a marginal increase in low-income commuters on ferry connected routes.

Solving the initial pooled version of the model recovers idiosyncratic preferences over routes. If idiosyncratic preference were weak, workers would all want to live in the tract where rent is lowest. The revealed preferences of workers show a willingness to bear higher rents for a neighborhood that they prefer. While the benefits of the ferry are large relative to the rent change, few workers are willing to alter their home, work, or labor market participation decision to capture this surplus. This is because they are unlikely to have idiosyncratic preferences that align with where the ferry is servicing. By moving, they sacrifice the utility gained by being in the neighborhood they would otherwise prefer. The reason high-income workers are more likely to switch routes is that their idiosyncratic preferences are more likely to align with the ferry routes.

The model solution reveals that ferry routes align with the idiosyncratic preferences of high-income workers more so than low-income workers. Table 9, column 1 tests for a correlation between idiosyncratic route parameters ($\chi_{s(i)jk}$) and whether the route was selected for ferry service. I standardize the route preference parameters for each worker-type to be mean zero and standard deviation equal to one. I look across routes

[15] A government report of the effects of the initial East River Ferry line found an increase in local residential property values around terminals (NYCEDC, 2013).

with at least one commuter of that type, as these have defined preference parameters. Column 1 shows the result of a cross-sectional regression of $\chi_{s(i)jk}$ against a dummy variable for whether that route had a ferry connection by the end of the study period. Routes treated by a ferry had a preference parameter 1.4 standard deviations above the mean for low-income workers, but 1.8 standard deviations above the mean for high-income workers. Because ferry-serviced areas are generally central, high-amenity areas, both groups have a preference to live or work along ferry-serviced routes, relative to the average city route, and are willing to bear higher rents to live there. However, high-income workers have a stronger bias towards these routes.

Table 9: Correlation of Ferry Treatment Status and Recovered Idiosyncratic Route Parameters ($\chi_{s(i)jk}$)

	Route Level	Home Tract	Work Tract
	(1)	(2)	(3)
		Low-income Workers	
Ferry link dummy	1.409**	0.868**	0.323
	(0.082)	(0.222)	(0.234)
N	2,467,060	2,124	2,158
		High-income Workers	
Ferry link dummy	1.773**	1.274**	0.897**
	(0.062)	(0.221)	(0.232)
N	1,823,702	2,124	2,160

Significance levels: $*$: 5% $**$: 1%. Robust standard errors shown in parenthesis.

I subsequently break out the differences in preference by home and work tracts. I take the weighted average of the preference parameters across routes, collapsed to the tract. When calculating average home tract preference I weight by the number of residents, and for work tract preference I weight by number of jobs. I recover the average route preference for every home and work tract, completing separate calculations for low and high-income workers. I regress the normalized tract preference level against whether that tract was provided a ferry terminal by the end of the study period. For preference over home tracts (column 2), I find that both low and high-income workers are willing to pay higher than average rents to live in the tracts that gained a ferry terminal, but the preference is stronger for high-income workers. Having a ferry connection is correlated with a 0.87 standard deviation increase in low-income worker home location preference but a 1.27 standard deviation increase for high-income workers. For work location preference (column 3), I find low-income workers have no preference towards working in ferry-serviced tracts, whereas high-income workers are significantly more amenable to working in ferry-serviced tracts. The correlation between revealed location preference parameters and ferry service confirms that ferry locations were directed to places where high-income workers prefer to live and, in particular, prefer to work.

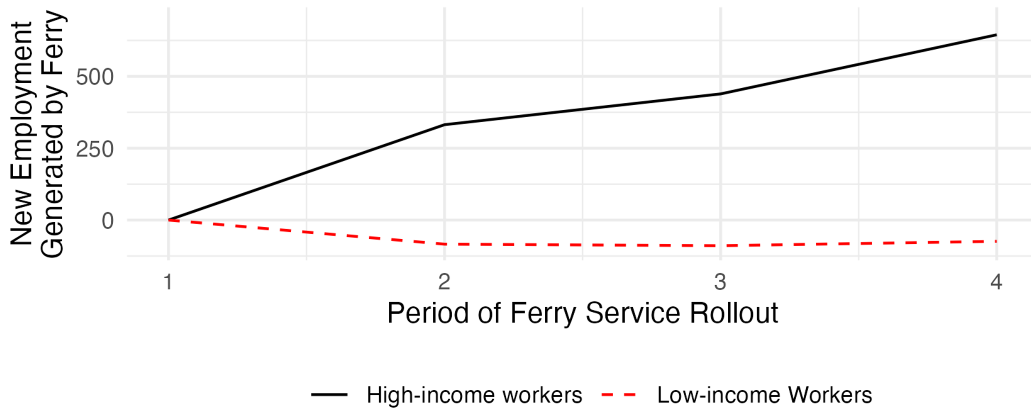
Table 9 results arise from ferry terminals being located in neighborhoods popular among high-income residents (eg Williamsburg) and popular work destinations for high-income workers (eg Wall Street). The distribution of idiosyncratic location preferences makes high-income workers much more willing to substitute towards ferry serviced routes relative to low-income workers.

The results of the model also yield shifts in the share of workers who are employed relative to those out of the workforce. After the ferry service is fully implemented, the model solution indicates 645 high-income workers moving into the labor force and 74 low-income workers exiting the labor force. Across the entire workforce, the change amounts to a rise in the city-wide employment rate of 0.01%. I estimated that 2,600 new labor market connections were generated by the ferry system. Therefore, reconciling the regression and structural results implies that 22% of the new labor market connections were the result of workers entering the labor force because of the transit improvement, while 78% of new connections were from already employed workers altering either their home or work location to benefit from a ferry commute. The model solution implies that ferry service actually reduced city-wide low-income worker employment, in contrast with stated policy goals.

Figure 6 graphs the number of workers who became employed due to the availability of ferry service. The figure shows changes as the ferry routes are rolled out in phases. For high-income workers, each expansion raises aggregate employment, with the initial expansion (The East River Ferry route) having the largest effect. The initial East River Ferry route marginally reduces low-income employment, as low-income workers had low idiosyncratic preferences for the terminals of this route, and local rent increases repel low-income workers from the central neighborhoods serviced by the route, displacing them to more isolated areas where they are more likely to exit employment. The subsequent route expansions had a negligible effect on low-income worker employment.

At the end of the study period, there were 841 low-income workers and 4,033 high-income workers with commutes between tract pairs connected by NYC Ferry. At this point, 53% of workers city-wide were earning above $40,000 annually, but 83% of workers on ferry-treated routes were earning above $40,000. Using the estimated annual benefits of access to a ferry route ($\chi_{s(i)\mathbb{1}}$), I estimate that the ferry service provides $645,000 in annual benefits to low-income workers who can commute directly

Figure 6: Number of Workers who Became Employed Due to Ferry Service



Model results deliver estimated changes in aggregate employment. Period one corresponds to no ferry service, and subsequent periods represent each discrete expansion of ferry service, as recorded in Figure 2. When all six routes are operating, the new equilibrium implies a net employment increase of 571 workers.

through the ferry system, compared to $4.3 million for high-income workers. This only accounts for benefits among those whose home and work census tracts are directly linked through the ferry service. However, the figures give an idea of the distribution of direct commuting benefits, with 87% of benefits accruing to the high-income group. These direct benefit estimates are small in comparison to the annual cost of providing ferry service, which was estimated to be $105 million.

6 Conclusion

Estimating the impact of a new transit system is complicated by endogenous worker decisions. I provide a method for estimating the impact of New York City's ferry service expansion on the local workforce. I distill lessons from recent structural models that deal with new transit infrastructure and panel bilateral commuter flow data (Tsivanidis, 2023; Severen, 2023; Dingel and Tintelnot, 2020; Tyndall, 2021). I propose a simplified model that has limited data requirements and a parsimonious solution strategy. The use of structural estimation models in similar scenarios could provide valuable insight into the impacts of new transit systems.

Detailed commuter flow data is available across the US through the LEHD LODES as well as the Census Transportation Planning Products (CTPP). LODES data is now available for 19 years, with annual updates continuing. I leverage multiple years of data to estimate route-by-worker-type preference parameters. The issue of sparseness in large commuting matrices continues to be a topic of econometric concern in spatial structural estimation of commuting flows. I propose a pooling method that greatly reduces matrix sparseness. I contribute to the development of empirical methods that leverage longitudinal variation to estimate the total impacts of new transit infrastructure. Deriving reasonable parameters of worker preferences for transportation links could also inform future analyses that estimate the impact of hypothetical future transportation systems. Recovering a full matrix of commuter preference parameters could allow infrastructure planning to target benefits at particular populations by providing infrastructure on routes they are likely to use.

A limitation of estimating route preferences with multiple years of pooled data is it requires an assumption that worker preferences across routes are stable over time. As neighborhoods evolve, the spatial preferences of workers will change. Estimating preferences on pooled data implies a trade-off between avoiding matrix sparseness and introducing data that may not reflect current preferences.

The effectiveness of NYC Ferry was the topic of significant policy debate. Of interest was whether the service improved labor market connections within the city and whether these benefits accrued to low or high-income workers. I provide some answers to these policy questions. I find the ferry service had a statistically significant but small effect on commuter flows within the city. I estimate roughly 2,600 workers altered their behavior to take advantage of the reduced commuting costs offered by the ferry service. All net commuting growth was among workers with incomes of $40,000 or higher. Results from the structural model show low and high-income workers both value a ferry connection. Initially, high-income workers were overrepresented on routes selected for ferry service, causing much of the benefit to accrue to high-income workers. Additionally, the location preferences of high-income workers aligned more closely with ferry routes, resulting in a shift of high-income workers towards ferry serviced routes. I find no evidence that the ferry system was successful in expanding low-income employment.

Commuting route preference differences across income groups are important determinants of who is served by a particular piece of transportation infrastructure. Designing equitable transit systems requires spatially targeting infrastructure to routes where there is a demand among the workers who are intended to benefit from the system.

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Appendix

Table A1: Effect of Ferry Connection on Commuter Flow: Two-way Fixed Effect Model

	All Workers (1)	Low-income (2)	High-income (3)
Ferry link dummy	3.006**	0.161	2.845**
	(0.541)	(0.095)	(0.507)
Year fixed effects	Y	Y	Y
Home-work pair fixed effects	Y	Y	Y
Home tract time trends	N	N	N
Work tract time trends	N	N	N
N	82,294,092	82,294,092	82,294,092
Pre-treatment average	6.181	1.656	4.525
% change	+48.6%	+9.7%	+62.9%

Significance levels: $*$: 5% $**$: 1%. Robust standard errors are shown in parenthesis.

Table A2: Effect of Ferry Connection on Commuter Flow: Two-way Fixed Effect Model with Home and Work Location Time Trends

	All Workers (1)	Low-income (2)	High-income (3)
Ferry link dummy	2.140**	0.047	2.094**
	(0.512)	(0.092)	(0.471)
Year fixed effects	Y	Y	Y
Home-work pair fixed effects	Y	Y	Y
Home tract time trends	Y	Y	Y
Work tract time trends	Y	Y	Y
N	82,294,092	82,294,092	82,294,092
Pre-treatment average	6.181	1.656	4.525
% change	+34.6%	+2.8%	+46.3%

Significance levels: $*$: 5% $**$: 1%. Robust standard errors are shown in parenthesis.

Table A3: Effect of Ferry Connection on Commuter Flow, Sample Limited to Waterfront Tracts

	All Workers (1)	Low-income (2)	High-income (3)
Ferry link dummy	2.543**	0.277*	2.266**
	(0.405)	(0.100)	(0.)
Year fixed effects	Y	Y	Y
Home-work pair fixed effects	Y	Y	Y
N	10,931,112	10,931,112	10,931,112
Pre-treatment average	10.036	3.434	6.602
% change	+25.3%	+8.1%	+34.3%

Significance levels: $*$: 5% $**$: 1%. The estimation approach follows Callaway and Sant'Anna (2021). Standard errors are shown in parenthesis. The analysis includes a balanced panel of routes where the home tract fronts a river or the ocean.

Table A4: Effect of Ferry Connection on Commuter Flow, Sample Limited to Ferry Treated Home Tracts

	All Workers (1)	Low-income (2)	High-income (3)
Ferry link dummy	2.322**	0.241*	2.081**
	(0.392)	(0.096)	(0.363)
Year fixed effects	Y	Y	Y
Home-work pair fixed effects	Y	Y	Y
N	1,149,048	1,149,048	1,149,048
Pre-treatment average	10.095	3.397	6.698
% change	+23.0%	+7.1%	+31.1%

Significance levels: $*$: 5% $**$: 1%. The estimation approach follows Callaway and Sant'Anna (2021). Standard errors are shown in parenthesis. The analysis includes a balanced panel of routes where the home tract received a ferry connection by the end of the study period.