Of Tracks and Trails: How Accessible Green Spaces Reshape Communities*

Xiyue (Michelle) Li†

November 9, 2025

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Abstract

What happens to neighborhoods after urban greening takes root? In the United States, over 26,000 miles of abandoned rail lines have been converted into trails, with another 9,000 miles underway. I use the geography of abandoned railroads to study how decades of rail trail openings have changed neighborhoods. In Greater Boston, where I observe trail opening dates, housing values rise by 7% within a decade of opening, alongside a 1.8 percentage point increase in the college-educated share and little change in other socioeconomic measures. By the second decade, housing values rise by 19%, the college-educated share by 7.7 points, and household incomes by 14%, suggesting that early compositional shifts amplify over time. Across all metropolitan areas, where I observe rail trails but not date of opening, I conduct a long-differences analysis. I instrument for trail creation using inefficiently connected historical rail segments, identified by edge betweenness centrality. Estimates show that between 1970 and 2020, tracts with rail trails experienced 18% higher housing value growth and similar patterns of sorting, along with a 24% increase in housing supply.

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[*] I am grateful to Rema Hanna, Gabriel Kreindler, and Ed Glaeser for their continued support and guidance. Gordon Hanson, Charles Taylor, Mark Shepard, Wolfram Schlenker, Denise DiPasquale, Jennifer Hochschild, Dave Donaldson, and Marcos Barrozo provided invaluable insights. I thank Juan Dodyk, Ankita Shirahatti, and participants of the Occasional Workshop in Environmental and Resource Economics, the Harvard Seminar in Environmental Economics and Policy, the Harvard Economics and Social Policy Graduate Student Workshop, and the Harvard Graduate Student Workshop in Labor/Public Economics for thoughtful feedback. I thank Forgotten Lands, Places, and Transit for sharing their data, and the staff at Rails-to-Trails Conservancy and MassTrails for helpful contextual information. I gratefully acknowledge financial support from the Malcolm Wiener Center for Social Policy and the Harvard Joint Center for Housing Studies. All errors my own.

[†] Harvard University, Cambridge, MA. Contact: xli@g.harvard.edu.

1 Introduction

Does urban greening move housing markets? Green spaces are prized features of the urban landscape; real estate listings highlight them, and studies link access to improved health and social outcomes.[1] Green space availability is also positively correlated with neighborhood socioeconomic status, reflecting several mechanisms.[2] Green spaces may have amenity value that gets capitalized into land and housing prices (Rosen 1974). Greening may coincide with other place-based investments that attract higher-income, more educated residents (Kuminoff et al. 2013). As wealthier households move in, local amenities may adjust to match their tastes (Couture & Handbury 2023). In the United States, a popular urban greening strategy is the conversion of former rail lines into multi-use trails: more than 26,000 miles of abandoned rail have been repurposed, with another 9,000 miles in development.[3] Despite their long history, ongoing development, and wide geographic reach, studies on the impacts of rail trails have largely been limited.[4]

In this paper, I estimate the effects of rail trail openings on neighborhood prices and composition in the Boston metropolitan area and at a national scale. I assemble detailed spatial data on abandoned rail corridors, active rail lines, and multi-use trails across the United States and link them to a boundary-consistent panel of census tracts. The analysis focuses on two domains: (1) housing market outcomes: log median housing values and housing supply, and (2) evidence of sorting: owner-occupancy share, college-educated share, log median household income, and White share.

I begin by focusing on Greater Boston, a region with both a rich history of rail trails and ongoing expansion efforts. Using the Massachusetts Department of Transportation's (MassDOT) trail inventory data, I identify rail trails as all planned and existing multi-use trails that follow abandoned rail corridors. I then compile opening dates at the trail segment level to determine the first year of trail access within each census tract. This allows me to

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[1] Heat and urban heat islands are associated with higher risks of illness and mortality (Chakma et al. 2024, Bian 2025). The environmental health literature suggests green spaces improve physical and mental health (Astell-Burt et al. 2013, Giannico et al. 2024), promote childhood development (Liao et al. 2019), increase community cohesion (Jennings & Bamkole 2019), and enhance public safety (Schertz et al. 2021).

[2] Across the 100 largest cities in the United States, low-income neighborhoods average 42 percent less park acreage per person than high-income neighborhoods, while predominantly minority neighborhoods have an average of 44 percent less park acreage than predominantly white neighborhoods (Chapman et al. 2021). This trend is similarly observed when extending to more generalized definition of natural environments (Klompmaker et al. 2023)

[3] Multi-use trails are paths typically pedestrian and bicycle corridors physically separated from roadways, designed for recreation and transportation.

[4] The first rail trails were built in the 1960s, and they currently exist in all 50 states. Existing studies on the impacts of rail trails tend to focus on single high-profile projects such as New York's High Line or the Atlanta BeltLine (Black & Richards 2020, Levere 2014, Noonan 2012, Immergluck & Balan 2018, VanCeylon & Melstrom 2025).

build a tract-by-year panel of first rail trail openings in Greater Boston.

Using this dataset, I estimate a staggered-adoption event study that exploits variation in the timing of trail openings to trace dynamic neighborhood responses over subsequent decades. In my main specification, I restrict the sample to tracts along existing or planned corridors to improve comparability between treated and control areas. I use the Sun & Abraham (2021) interaction weighted estimator, where I compare treated tracts with never/not-yet-treated tracts of the same year. Identification relies on a parallel trends assumption: conditional on census tract and year fixed effects, outcomes in tracts receiving a trail opening would have evolved similarly to those in not-yet-treated tracts in the absence of treatment. Across all outcomes, pre-trends are flat, indicating no evidence of anticipatory effects.

I find that trail openings are rapidly capitalized into nearby housing markets. Relative to control corridors, median housing values rise by 7% within the first decade after opening, by 19% within the second decade, and by 23% within the third.[5] College educated residents appear to be among the first movers: the college-educated share increases by 1.8 percentage points within the first decade (statistically significant at the 10% confidence level), by 7.7 percentage points in the second decade, and by 9.7 percentage points in the third. Early gains in housing value and shifts in neighborhood composition appear to set in motion slower-moving changes in neighborhood trajectories. Although housing supply increases each decade, growth is relatively slower in treated tracts. It is 5% lower (significant at the 10% level) in the second decade and 11% lower in the third. Median household income shows little change initially but rises by 14% in the second decade and 15% in the third. The owner-occupancy share increases by 3.7 percentage points in the third decade. The White population share shows no statistically significant change across the three post-treatment decades.

Taken together, these results suggest that rail-trail investments generate immediate amenity value, attracting more educated residents. Consistent with evidence that spatial sorting can occur along education lines (Diamond 2016), these early, rail trail-induced changes appear to catalyze further sorting, with large numbers of higher-income households moving in subsequent decades. The slowdown in housing supply expansion is suggestive of a story of homeowner opposition to new development in places with high demand, consistent with evidence of NIMBYism and supply constraints in gentrifying neighborhoods (Fischel 2001, Gyourko & Molloy 2015).

To assess external validity, I conduct a second analysis to study the impacts of rail trails on the contiguous United States. At the national scale, the main challenge is finding an

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[5] "First decade" refers to 0–9 years after opening and corresponds to Decade 0 in Figures 5–10. Prior and subsequent decades are defined analogously.

exogenous source of variation to identify causal effects. Because trail opening dates are not consistently available nationwide, I cannot replicate the event-study design. I address identification in two ways. First, I use a long-differences design to study how changes in trail presence relate to long-run changes in outcomes. In this approach, any tract with a trail today is treated as having received a trail at some point between 1970 and 2020, and I compare these tracts to those that did not gain a trail over the same horizon.[6] This design captures the cumulative effects of trail creation while differencing out time-invariant unobservables.

As is, changes in trail presence over this period would still be endogenous, since the likelihood of trail creation is tied to local economic conditions. To generate exogenous variation in trail construction, I predict rail segment abandonment using a network analysis approach in the spirit of Faber (2014). I reconstruct the American rail network at its historical peak by combining present-day active and abandoned lines into a single network and enforcing noding at all crossings and end points.[7] I predict abandonment using an algorithm that calculates edge betweenness, a measure of how often a segment lies on the shortest path between two nodes. Intuitively, segments with high betweenness are central connectors in the network, while low-betweenness segments contribute little to overall connectivity, and would be more likely to be abandoned when demand for transport by rail declines. Using this network-geometry logic, I flag "predicted abandoned" as the 45% of total rail mileage with the lowest betweenness, consistent with the U.S. rail decline from 254,000 to 140,000 miles today. Linking these predicted abandoned segments to census tract boundaries yields a tract-level indicator for presence of rail abandonment, which I use as an instrument for trail creation between 1970 and 2020.

A key identifying assumption is that predicted rail abandonment predicts subsequent trail conversion but is orthogonal to unobserved time varying factors that impact long-run neighborhood change (e.g. local economic trends correlated with actual rail abandonment and modern day socioeconomic outcomes). I argue that since the instrument is purely based on network geometry, after controlling for county fixed effects and a rich set of baseline geography/economic controls, the predicted abandonment indicator is plausibly exogenous to other omitted factors affecting the outcomes. A second identifying assumption is that, conditional on controls, the only channel through which predicted abandonment affects outcomes over

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[6] This assumption is justifiable because the vast majority of rail trails were built after 1980, when legislation was introduced to support rail to trail conversions. Officially, the first rail trails were constructed in the 1960s, but to the best of my knowledge, only two are documented to have been built before 1970. I discuss this in more detail in Section 2.

[7] Since large-scale rail construction and abandonment did not overlap (Harnik 2021), I argue that this method provides a near-complete picture of the American rail network at its peak.

1970–2020 is via actual trail creation. This condition would be violated if abandoned rail itself puts neighborhoods on different trends relative to places with no rail. I show evidence that abandoned rail minimally, if at all, impacts economic development on its own.

Applying the IV long-differences strategy, I estimate sizable effects of rail-trail creation on long-run neighborhood change. On the housing market side, tracts that gained a trail between 1970 and 2020 experienced an 18 percent increase in median house values and a 24 percent increase in housing supply.[8] On the demographic side, trails are associated with a 14 percent increase in median household income, a 5.3 percentage-point increase in college educated share, and a 7.7 percentage-point increase in the White share of the population, consistent with evidence of sorting.

The evidence suggests that rail trails catalyze economic revitalization, while also reproducing familiar patterns of gentrification. Housing values rise substantially, indicating strong capitalization effects as households are willing to pay more for trail access. At the same time, shifts in income, education, and racial composition point to sorting, with more educated, higher-income, and White households disproportionately moving into trail neighborhoods. I caveat that the effects likely reflect both trail value and the neighborhood change it sets in motion. Existing literature suggests that as higher-income and college-educated households move in, further sorting and reinvestment amplify price growth (Couture & Handbury 2023, Couture et al. 2024). I interpret these estimates as trail-catalyzed neighborhood change, even if the underlying mechanisms evolved endogenously over time.

While the estimated long-run effects may appear large, they are in line with evidence from other high-profile urban greenways. For example, Black & Richards (2020) document housing price gains of 35 percent around the New York High Line. Immergluck & Balan (2018) examine the Atlanta BeltLine using hedonic price functions, estimating that homes within a half-mile of the Atlanta BeltLine are about 19.2 percent more valuable than comparable homes elsewhere, the median effect across project segments. These estimates are broadly comparable to the 18 percent average capitalization effect estimated here. That ordinary rail trail conversions produce impacts of a similar order of magnitude highlights their significance as a general public amenity, not just as high profile projects.

This paper contributes to the literature in three ways. First, it extends research on the economic and social effects of open and green spaces. Prior work on open space highlights the value of land conservation and preservation to nearby residents (Walsh 2007, Lang 2018, Wu et al. 2023), while studies of specific urban greenways find substantial local capitalization effects (Black & Richards 2020, Levere 2014, Immergluck & Balan 2018, Noonan 2012). I

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[8] The expansion of supply, a reveral from the Greater Boston event study, is possibly a reflection of differences in zoning restrictions across metropolitan areas. I explore some reasons for this in the Appendix.

contribute to this conversation by examining how the re-greening of post-industrial areas affect neighborhood trajectories. I also broaden the scope of existing work. By analyzing a large and diverse set of rail-to-trail projects across cities, this paper is, to my knowledge, the first to provide metropolitan- and national-level evidence on how urban greening shapes neighborhood change.

Methodologically, the paper builds on the literature on quasi-experimental designs to estimate the capitalization of amenities and disamenities into housing prices. Foundational studies exploit discontinuities or quasi-random variation to identify willingness to pay for local attributes, including schools (Black 1999), environmental quality (Leggett & Bockstael 2000, Bui & Mayer 2003, Chay & Greenstone 2005, Greenstone & Gallagher 2008, Gamper-Rabindran & Timmins 2013, Linn 2013, Cassidy et al. 2022, Guignet & Nolte 2024), and other local public goods and risks (Bowes & Ihlanfeldt 2001, Pope 2008, Linden & Rockoff 2008, Andersson et al. 2010, Muehlenbachs et al. 2015, Diao et al. 2017). A broader methodological discussion emphasizes the challenges of identification in hedonic models (Banzhaf 2021, Bishop et al. 2020). This paper adds to that tradition by applying a novel network-based identification strategy that leverages variation in the historical geography of abandoned rail lines to predict green space development, addressing the endogeneity of siting decisions that complicates hedonic valuation of urban green space.

The findings also extend the literature on environmental justice and neighborhood sorting. Existing work emphasizes how improvements in environmental quality has heterogeneous impacts by population. Studies of brownfield remediation, pollution abatement, and natural disasters highlight that environmental improvements can reshape community composition and exacerbate inequality (Haninger et al. 2017, Banzhaf et al. 2019, Bakkensen & Ma 2020). Building on frameworks of residential sorting (Tiebout 1956, Banzhaf & Walsh 2013), and recent evidence on heterogeneity in preferences for environmental amenities and local public goods (Lang & VanCeylon 2025, Depro et al. 2015, Daepp et al. 2023), I show that the creation of new green space, which generally requires local buy-in, not only raises property values but also influences neighborhood composition, with implications for equity and inclusion in urban development.

The rest of the paper proceeds as follows. Section 2 provides background and institutional details of rail trails in the United States. Section 3 presents an event study of rail trail openings in Greater Boston. Section 4 discusses the construction of the predicted rail abandonment instrument and presents the results of long-term impacts nationally. Section 5 concludes.

2 Background

2.1 Multi-Use Trails as a Public Amenity

Multi-use trails, also referred to as shared-use paths, greenways, or linear parks, are paths designed for non-motorized users with exclusive right-of-ways and with minimal cross flow by motor vehicles. They are often located along rivers, streams, ridgelines or on historic infrastructure corridors such as canals or railroads, features that shape urban form (Lindsey et al. 2008). Unlike hiking trails in the wilderness, multi-use trails are designed to link people and places.

Supporters argue that trails offer a wide range of benefits, functioning both as recreational amenities and as essential components of active transportation networks.[9] Planners advocate for these greenways to improve city landscapes, conserve natural habitats, support biodiversity, and provide opportunities for recreation and fitness. Additionally, they serve to connect communities to each other and to existing public transit infrastructure, reduce emissions in transportation, and reduce road congestion (Keith et al. 2018).

While the concept of greenways can be traced back to the 19th-century parkway and greenbelt movements initiated by Frederick Law Olmsted, it is only in recent decades that multi-use trail networks have seen significant expansion. This resurgence can largely be attributed to shifts in economic and demographic factors that prioritize quality-of-life amenities, heightened public awareness of the health benefits associated with active transportation, and increased policy emphasis on climate resilience and equitable urban development (Lindsey et al. 2008).

Today, many jurisdictions view multi-use trails as tools for economic development. They are seen as catalysts for increasing property values, boosting tourism, and revitalizing historically underserved areas.[10] For this reason, multi-use trails have become integral to contemporary planning objectives around recreation, transportation, and sustainability.

As a reflection of this growing recognition, funding for multi-use trails has increased at both federal and state levels in recent years. Federally, the Transportation Alternatives (TA) program stands as the largest dedicated source of funding for trails and active transportation projects. The 2021 Bipartisan Infrastructure Law authorized an average of \$1.44 billion per year over five years for TA projects, including pedestrian and bicycle facilities (Federal Highway Administration 2021). Additionally, the Active Transportation Infrastruc-

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[9] Active transportation is defined as human-powered mobility, such as biking or walking, which is an alternative to motor vehicle based transportation (United States Department of Transportation 2022).

[10] This understanding is based on conversations with representatives from MassTrails and the Rails-to-Trails Conservancy.

ture Investment Program, included as part of the Fiscal Year 2023 Omnibus Appropriations, granted \$45 million to accelerate local and regional plans to build walking and biking paths and trails to everyday destinations (Federal Highway Administration 2025).

Many states have also established their own funding mechanisms for multi-use trail projects. For instance, Massachusetts' MassTrails program provides grants to support recreational trail and shared-use pathway projects across the Commonwealth, focusing on projects that demonstrate critical network connections of regional or statewide significance (MassTrails 2025). Similarly, in 2024, Connecticut awarded \$10 million in grants to support the development and improvement of 45 multi-use trails located in towns and cities throughout the state (State of Connecticut 2024). These investments suggest that multi-use trails are considered to be salient public amenities by planners and policymakers.

2.2 Heterogeneity in the Benefits of Multi-use Trail Development

Multi-use trails are recognized for their contribution to the sustainability and economic vibrancy of cities, as well as the health of its residents. Recent research underscores the benefits of green spaces, highlighting their role in enhancing physical and mental health (Astell-Burt et al. 2013, Giannico et al. 2024), supporting childhood development (Liao et al. 2019), fostering community cohesion (Jennings & Bamkole 2019), and improving public safety (Schertz et al. 2021).

Multi-use trails have been touted as public goods that can significantly influence local property values and attract private investment. However, such benefits can have uneven distributional impacts. While these projects aim to address environmental justice issues by improving neighborhood well-being and aesthetics, they can inadvertently drive up housing costs and attract wealthier residents, displacing the very communities they were designed to benefit (Wolch et al. 2014, Maantay & Maroko 2018, Asabere & Huffman 2009). Rising property values around trail developments can generate substantial economic gains for property owners, yet they may also lead to increased housing costs, affordability pressures, and displacement risks for lower-income and historically marginalized residents.

The Atlanta BeltLine exemplifies both the potential benefits and challenges of multi-use trail development. Initially proposed in 1999 as a comprehensive strategy to address Atlanta's economic segregation, environmental justice concerns, air pollution, and infrastructure deficiencies, the project aims to transform a 22-mile former railway loop into an interconnected network of pedestrian and bicycle trails, linking 45 neighborhoods across the city's core (Hochschild 2024, Weber et al. 2017).

Since construction began in 2008, the BeltLine has sparked significant economic activity, attracting over \$9 billion in private development by the end of 2023 (AtlantaBeltline 2024).

One example is the Reynoldstown neighborhood, adjacent to the Eastside Trail, where redevelopment has reshaped the area. A former steel mill, sold in 2020, has since been replaced with over 60 new housing units, including condos and townhomes (Atlanta 2025).

However, the BeltLine's impact has not been uniformly positive across communities. While the project has stimulated local economies and expanded recreational opportunities, it has also increased housing costs and displacement pressures for lower-income residents. Immergluck & Balan (2018) estimate housing price values to have increased by 17.9 percent and 26.6 percent more for homes within a half-mile of the BeltLine than elsewhere, and that the increase in median sale price was the highest near the southwest segment, a historically black neighborhood of Atlanta. Noonan (2012) also studies the BeltLine, finding short-run gains in property values that primarily benefit existing owners, while longer-term impacts remain ambiguous.

Thus, while the BeltLine is regarded as a success in expanding recreational access and increasing Atlanta's property tax base, its development also demonstrates the heterogeneous effects of multi-use trails. Understanding the trade-offs between green space development and its impact on equitable growth is crucial for policymakers seeking to balance sustainability goals with other needs of vulnerable populations.

2.3 Rail Trails in the United States

While not all multi-use trails are rail trails, many, like the Atlanta BeltLine, are constructed along abandoned railway corridors due to their availability and relative convenience. At its peak in 1916, the United States rail network spanned over 250,000 miles, serving as the primary mode of freight and passenger transportation (Harnik 2021). Over subsequent decades, however, railroads began to lose their dominant position. Between 1930 and 1960, the rise of air and automobile transportation diverted both freight and passengers away from rail. Compounding this shift was the country's transition from coal to oil in the 1960s, which undermined a major segment of rail traffic—particularly in the eastern United States—and led to the bankruptcy of six major northeastern railroads between 1967 and 1972 (Ferster 2006). Rail abandonment further accelerated after the Staggers Act of 1980, which substantially loosened the restrictions on rail abandonment. As a result, between 1980 and 1990, the rate of rail abandonment by major carriers accelerated to between 4,000 and 8,000 miles per year (Ferster 2006).

There are strong complementarities between abandoned rail corridors and multi-use trails. Rail corridors typically feature gentle gradients, multiple points of access, separation from vehicular traffic, and proximity to nature, providing an ideal foundation for socially inclusive trails that accommodate a diverse range of users. Their linear connectivity is especially valuable for transportation, which is otherwise challenging to achieve in developed spaces. Thus, repurposing inactive rail lines significantly reduces the costs of multi-use trail development, as the existing infrastructure minimizes the need for extensive land acquisition and grading.

The concept of a rail to trail conversion emerged formally in the 1960s. Notable examples include the Elroy-Sparta State Trail in Wisconsin and the Illinois Prairie Path, which were among the pioneering projects to transform defunct rail corridors into recreational trails. However, the rail trail movement didn't gain significant momentum until the 1980s with the passage of the National Trails System Act Amendments of 1983, which introduced the concept of "railbanking." This allowed railroads to transfer unprofitable lines to qualified public or private agencies for interim trail use, while reserving the option to restore rail service in the future.[11] This legal framework made it easier to convert abandoned rail corridors into trails, leading to the creation of over 26,000 miles such trails (Rails to Trails Conservancy 2025).

Rail trails offer a compelling opportunity to study green space development. First, with abandoned rail lines distributed across the United States, their conversion into trails has become widespread, creating opportunities to study their impacts at scale. Second, because these trails are constructed along former rail corridors, whose original routing was often shaped by engineering constraints and topography (Clarke 1893), they provide a promising setting to study the causal effects of new green space. While trail development is not random, the distribution of the historical rail network introduces spatial variation that can be leveraged for causal inference.

Figure 1 illustrates the strong relationship between abandoned rail corridors and multi-use trail siting in the Greater Boston Area. Although not every trail follows an abandoned railway and not all abandoned railways are converted to trails, the figure highlights the strong correlation between the two. Figure 2 extends Figure 1 by presenting the distribution of rail and trail lines across the contiguous United States. The widespread nature of rail to trail developments allows me to analyze at a large scale the impact of green amenities on surrounding communities.

3 Dynamic Effects in Greater Boston: Event Study Evidence

I begin by testing the hypothesis that rail trails function as valued amenities that increase housing demand. An alternative explanation is selection: trails may be sited in places already on favorable economic or demographic trajectories, so observed post-opening increases in prices or incomes could reflect underlying neighborhood trends rather than a response to

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[11] In practice, very few disused rail corridors saw rail service start up again.

the trails themselves. Because trails are built along abandoned rail lines, it is also useful to assess whether the presence of abandoned rail, prior to conversion, affects housing demand or neighborhood quality.

I conduct an event study of rail trail openings in the Greater Boston area.[12] I focus on this region due to its relatively high density of abandoned rail corridors and long history of rail-to-trail conversions, which provide rich variation in the timing and location of trail openings. Massachusetts has also actively supported shared-use path expansion through its Priority Trails Network Vision, which seeks to establish a connected multi-use trail network through key areas across the state. Since 2019, the state has distributed grants focused on extending and linking existing trails, making Greater Boston a particularly relevant and timely case study.

In my main analysis, I restrict the sample to tracts along existing and planned rail trail corridors. This information is provided by MassTrails, the state's inter-agency initiative dedicated to building multi-use trails. The data consists of completed, under-construction, and proposed segments that support the state's trail development goals, allowing me to estimate effects within the policy-relevant universe of trail corridors. I also conduct a broader analysis that compares tracts experiencing trail openings to all other tracts in the region, estimating effects relative to the overall housing market.

The event study framework allows me to test for pre-existing trends and isolate the timing of trail-related effects. If tract-level housing prices or demographic characteristics remain stable in the years leading up to a trail opening, then omitted variables and anticipatory effects are likely not driving changes in demand. In the full sample, this further means that neighborhoods with abandoned rail is not evolving on a different trajectory relative to neighborhoods with no rail. Further, if shifts in housing prices or population composition occur only after trail access is introduced, this provides evidence that subsequent effects are catalyzed by the rail trail.

3.1 Data

Population and Housing Characteristics. I use the 1970-constant census tract panel developed by Glaeser et al. (2025), which harmonizes tract boundaries from 1970 to 2020. This ensures geographic consistency in measuring long-run changes in key economic variables, such as median housing values. I log-transform median housing value, median household income, and housing supply to reduce skewness and mitigate the influence of outliers.

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[12] Towns and cities included in this analysis: Randolph, Stoneham, Winchester, Chelsea, Weymouth, Norwood, Somerville, Milton, Saugus, Watertown, Canton, Wakefield, Revere, Waltham, Woburn, Newton, Arlington, Belmont, Cambridge, Lincoln, Medford, Melrose, Boston, Needham, Dover, Westwood, Lexington, Braintree, Quincy, Wellesley, Holbrook, Weston, Hingham, Everett, Brookline, Malden, Lynn, and Dedham.

Abandoned Rail and Multi-Use Trail Data Abandoned rail data comes from Forgotten Lands, Places, and Transit (FRRandP), a crowd-sourced dataset tracking abandoned, disused, and out-of-service railroads. I rely on this database because it provides the most complete coverage of abandoned tracks, including older segments not always documented in official registries. Data on planned and existing shared-use paths data is from the Massachusetts Department of Transportation (MassDOT). To identify rail trails, I overlay the MassDOT dataset with the abandoned rail line data and classify a path segment as a rail trail if more than 50% of its length overlaps with an abandoned rail corridor. Recognizing that trails are sometimes extended beyond the footprint of the original abandoned rail line to improve connectivity, I also include contiguous segments identified by trail name, even if not directly built on former rail infrastructure.[13]

Because trails are often constructed and opened in phases, not all segments of each rail trail become operational simultaneously and some remain under active development. For each trail segment, I conduct original research, using historical records and satellite data to identify its opening year. Figure 3 illustrates the spatial distribution of rail trails in my area of analysis.

3.2 Empirical Strategy

I combine the trail data with longitudinal census data from 1970 through 2020, harmonized to 1970 boundaries. This approach ensures that I measure changes in housing prices and demographic characteristics within consistent geographic areas over time, so that I capture true neighborhood-level change rather than artifacts of redistricting. In each census tract that contains at least one rail trail segment, I determine the first year in which any segment of a rail trail within the tract opened. This serves as the event time. Table 1 lists the rail trail segments used to define treatment timing in the analysis.

In my preferred specification, I restrict the analysis to tracts that contain existing and planned rail trail corridors. This restricted design identifies effects within the policy-relevant universe of rail trail corridors. The resulting panel consists of 97 census tracts observed over 6 waves (1970 to 2020). Of these tracts, 76 have existing rail trails, which opened between 1970 and 2024. The remaining tracts have planned rail trails that have yet to be opened. A tradeoff of using 1970 census tracts is that I have a smaller sample size; many areas that were less densely populated in 1970, but experienced significant growth later, were subdivided into multiple tracts in subsequent decades. In Appendix B, I replicate the analysis using 1980-harmonized tracts as a robustness check.

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[13] For example, the Somerville Community Path was initially constructed in 1995 on the abandoned Fitchburg Cutoff rail line, but was extended along the MBTA Green Line extension in 2022.

To characterize the temporal variation in trail openings, I begin by plotting the distribution of event times for existing trails. Event time is defined as the difference between the census year and the corresponding trail opening year. Since the census is conducted every ten years, I group my event time into decade bins, as shown in Figure 4. Due to the limited number of observations in the 40–49 year and the ≥ 50 bins, I combine these categories with the category with the 30-39 year group into a single bin in my estimation.

Because rail trails opened at different times, I use the Sun & Abraham (2021) estimator, which compares treated tracts at each event time k to never-treated or not-yet-treated tracts in the same calendar year, then aggregates cohort-specific effects into an interaction-weighted average. The omitted period is the decade prior to trail opening; for example, if a trail opened between 1991 and 2000, the 1990 Census observation serves as the baseline. The event study specification is approximated by the following equation:

$$y_{it} = \sum_{g} \sum_{k \neq k_0} \rho_{gk} \, \mathbf{1}\big(G_i = g\big) \, \mathbf{1}\big(t - G_i = k\big) + \alpha_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where y_{it} is the outcome of interest (e.g., log median house value) in tract i and year t, G_i denotes the decade in which the first trail opened (the treatment cohort), and $k = t - G_i$ is the number of decades since treatment (event time). The coefficient ρ_{gk} represents the treatment effect for cohort g at relative time k. Tract fixed effects α_i and year fixed effects λ_t absorb time-invariant differences and common temporal shocks, respectively. I use Conley standard errors with a 2-mile spatial cutoff.

The identifying assumption of the event study is that, absent treatment, tracts with trail openings would have followed the same trajectory as tracts that receive treatment later. Parallel pre-trends imply that tracts along not-yet-opened or future trail corridors provide a credible counterfactual for tracts that received trails earlier, which would support a causal interpretation of the post-opening estimates.

In a separate full-sample analysis, I broaden the comparison group to include all tracts in the region, including those without abandoned rail. This specification estimates the effect of rail trail development relative to the wider housing market. I exclude tracts within one mile of the urban core, as central neighborhoods may follow distinct trajectories unrelated to trail development and could bias the results. In this setting, parallel pre-trends would indicate that neither the presence of abandoned rail corridors nor anticipatory dynamics are driving the observed effects. Post-opening changes can then be interpreted as reflecting the effect of new trail access relative to all tracts in the region.[14]

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[14] Figure A1 illustrates the spatial distribution of rail trails used in the full sample.

3.3 Results and Discussion

Estimates from the main analysis, which restricts attention to tracts along planned or existing rail trail corridors, are displayed in Figures 5 through 10. A first observation is that pre-trends are flat relative to the baseline across all outcomes, indicating that before trail opening, tracts were developing across similar trajectories. Further, they point to a lack of of anticipatory effects of rail trail opening, reinforcing the interpretation that households respond to actual trail openings rather than expectations. This is consistent with qualitative accounts of the development process: rail-trail projects typically require coordination across multiple jurisdictions and face legal or political delays that can last years.[15]

The economic outcomes are robust. Figure 5 shows that housing values rise immediately. Within the first decade of a rail-trail opening, house values increase by 7% relative to tracts without trails.[16]. This gap widens in subsequent decades. House values are 19% higher within the second decade, and 23% higher within the third decade relative to control tracts.[17] This suggests that the amenity value of the trail is immediately recognized, and tracts with trails tend to gain in value at much faster rates in subsequent decades.

The evidence suggests that the value of rail trail amenities induces sorting. Figure 8 shows that college educated residents appear to be among the first movers, as the college-educated share increases by 1.8 percentage points within the first decade (significant at the 10% confidence level), by 7.7 percentage points in the second decade, and by 9.7 percentage points in the third. The incomes of residents respond more gradually, as shown in Figure 9. There is no discernible income effect in the first decade of trail opening, but by the second decade, incomes are 14% higher within treated tracts relative to not-yet-opened corridor tracts, and the gap between treated and control units is stable at 15% in the third decade.

Early gains in housing values and compositional shifts appear to set in motion slower-moving changes in neighborhood trajectories. Housing supply declines by 5 percent (significant at 10 percent) in the second decade and 15 percent in the third, (Figure 6), while the owner-occupancy rate rises by 3.7 percentage points in the third decade (Figure 7). There is no statistically significant change in the White population share across the three

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[15] For example, the Minuteman Bikeway spanned roughly eighteen years from conception to completion—"seventeen years of politics and one year of construction," as one local planner put it (Harnik 2021).

[16] "First decade" refers to 0–9 years after opening and corresponds to Decade 0 the figures

[17] I do not show $k = +3$ coefficients in my event study plots. Due to a lack of observations, are driven almost entirely by two early projects near Davis Square: (1) the Alewife Linear Park Trail and (2) the initial segment of the Somerville Community Path, both built in the 1980s on opposite sides of Davis Square (The Watertown Linear Park, which opened in 1970, also falls in the $k = +3$ group but spans only one tract). Results indicate very high estimates of changes to housing value and income in the $k = +3$ bin, as well as deviation from the other post-treatment results. I argue that the $k = +3$ estimates likely capture localized dynamics in Davis Square rather than a generalized long-run effect of rail trails across the region, and should thus be interpreted cautiously. The point estimates can be found in Tables A1 and A2.

post-treatment decades.

In a separate analysis, I broaden the comparison group to include all tracts in Greater Boston outside of one mile of the urban core, including those without abandoned rail. Results are displayed in Figures A2 through A7. The direction of effects largely mirrors the corridor-based results, though standard errors are larger.[18]

Two differences are noteworthy. First, owner-occupancy rates (Figure A4) are consistently higher in tracts that eventually receive a trail, suggesting that projects were more likely to be sited in homeowner-heavy communities. This is consistent with local advocacy by residents with stronger stakes in neighborhood amenities. After openings, however, owner-occupancy actually decrease; post-treatment estimates fall to be statistically indistinguishable from zero until the third decade, when they exceed control tracts by 1.6 percentage points (significant at the 10 percent level). This pattern suggests that early demand may have drawn more renters to trail-adjacent areas, but homeowners again became more prevalent over time. Second, results for White share (Figure A7) are noisier: the White share appear to be somewhat higher decades before opening, but as standard errors include zero across most periods, there are no clear takeaways from the plot.

These results point to a story in which rail trails are immediately valued as amenities, with their benefits capitalized into nearby housing prices. Over time, however, differential preferences for green space appear to attract more educated and higher-income households, consistent with spatial sorting along socioeconomic lines (Diamond & Gaubert 2022, Couture et al. 2024). The increase in homeownership further implies that buyers in these neighborhoods have higher willingness to pay than investors, reinforcing evidence of sorting. The later decline in housing supply is consistent with homeowner opposition to new construction in high-demand neighborhoods, echoing theories of NIMBYism and supply constraints in gentrifying areas (Fischel 2001, Gyourko & Molloy 2015).

3.4 Comparison of Estimates with Capitalization of Other Public Amenities

I benchmark these estimates, with the capitalization of other public amenities into housing values. To identify a set of comparable studies, I focus on those evaluating discrete environmental improvements rather than long-term amenity growth. Because most hedonic estimates in my reference studies capture short-run capitalization rather than general-equilibrium adjustment, I take the initial 7 percent increase in nearby housing values as the relevant benchmark. Figure 11 summarizes these comparisons.

Information-based programs, such as TRI reporting or brownfield certification, show minimal effects on property values (Bui & Mayer 2003, Linn 2013). In contrast, remediation

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[18] Numerical estimates for both the corridor and full-sample analyses are reported in Tables A1 and A2.

of contaminated sites—such as Superfund or brownfield cleanups—yields larger increases (Greenstone & Gallagher 2008, Gamper-Rabindran & Timmins 2013, Cassidy et al. 2022, Guignet & Nolte 2024, Haninger et al. 2017). Among these, brownfield remediation seems especially relevant: although abandoned rail corridors are typically non-toxic and less visually blighting than brownfields, their transformation into greenways creates comparable local amenities. Haninger et al. (2017) estimate that cleanup raises nearby housing prices by 5 to 11.5 percent in the short run. In this context, a 7 percent capitalization effect from rail-trail conversions appears plausible.

Finally, I compare these effects to gains from transit access. Bowes & Ihlanfeldt (2001) find that new rail service in Atlanta increased nearby housing values by 3.5 percent within 2–3 miles of stations, while Diao et al. (2017) estimate an 8.6 percent increase for properties within 600 meters of new stations in Singapore. These regional differences likely reflect variation in urban form and amenity demand, but together they situate rail-trail capitalization within the broader range of environmental and infrastructure improvements.

4 Long Run Effects: Using Predicted Abandoned Rail to Instrument for Trail Presence

Do we see similar patterns of change induced by rail trails nationally? Ideally, I would apply the previous event study approach at a national scale, but doing so requires knowing all trail-opening dates by segment, which are not readily available. This limitation motivates the second part of this paper: a long-differences design that uses predicted rail abandonment to instrument for trail placement and examine differential growth between 1970 and 2020 across the contiguous United States.

4.1 Data

To estimate the effect of trail creation on community change, I combine census data with information on abandoned rail, active rail, and multi-use trails across the contiguous United States.

Abandoned, Active and Historical Rail. Abandoned rail data comes from Forgotten Lands, Places, and Transit (FRRandP), a crowd-sourced dataset tracking abandoned, disused, and out-of-service railroads. Active rail data comes from the North American Rail Network (NARN) Rail Lines dataset, which categorizes rail lines by type of operation. I subset on those categorized as “Main Line” and “Major Industrial Line.”

Rail Trail. Not every state keeps publicly available records of its trail inventory. Here, I use data from OpenStreetMap (OSM), filtered to identify paths intended for non-motorized, multi-modal transportation. Specifically, I include paths tagged as highway=cycleway, highway=footway, or highway=path. These tags represent trails primarily designated for cyclists, pedestrians, or general non-car use, respectively. To ensure that the selected trails are truly multi-use, I further filter for paths tagged for both "bicycle" and "foot", confirming they accommodate both cyclists and pedestrians. Additionally, I exclude trails marked for private access, as well as those designated for mountain biking or skiing, since they cater to specific recreational activities rather than general-purpose recreation and transportation. These refinements ensure that the dataset accurately captures accessible, multi-use trails that facilitate biking and walking—key components of greenways. To identify rail trails, I then overlay these OSM trails with a buffered map of abandoned rail lines, classifying a trail as a rail trail if it falls within the buffer of an abandoned rail corridor.

Population and Housing Characteristics. Consistent with the event study, I use the 1970-constant census tract panel developed by Glaeser et al. (2025), managed following the same procedures as in Section 3. Figure 12 shows the distribution of the 1970 census tracts, which defines the geographic scope of my empirical analysis. A limitation of this dataset for this analysis is that it begins in 1970, whereas the earliest rail trails opened in the 1960s. As a result, I cannot observe neighborhood changes that may have occurred during the first post-conversion decade, potentially missing part of the treatment effect if trails had immediate impacts on housing markets or demographics. No tract-level harmonization is currently available from 1960 to 2020, and constructing one would require aggregating to the much coarser 1960 tract definitions, which also cover a smaller geographic area. This is not an issue for the event study, since event times are directly observed.

Although there doesn't currently exist a record of historical rail trail openings, historical records suggest that only a few rail trails were built in the 1960s, with the rail trail movement gaining real momentum only in the 1980s. Thus, using 1970 as the baseline should serve as a sufficient pre-treatment period while enabling me to assess neighborhood change over time and across consistent space.

I merge the rail and trail data with these census tracts to code the presence of abandoned rail, active rail, predicted abandonment, and rail trails for each tract-year observation.

4.2 Instrument Construction

I predict rail abandonment using a connectivity-based algorithm.[19] This approach is inspired by that of Faber (2014), who instruments for the location of routes in China's National Trunk Highway System by modeling the system as a graph in which cities targeted for connection are nodes and routes are edges, and then predicting a least-cost network based on geographical features such as distance, land gradient, and terrain type.

My approach applies the same logic in reverse. I reconstruct a comprehensive pre-abandonment rail network by combining present-day active and abandoned rail lines into a single line network and enforcing noding at all crossings. This reconstruction is designed to approximate the U.S. rail system at its peak.[20] I combine present day active and abandoned rail data to build a map of the historical peak of the rail network.[21] The resulting connectivity structure then allows me to identify segments that were most redundant and therefore most likely to be abandoned.

To predict which segments would be abandoned, I employ a connectivity-based algorithm that calculates edge betweenness centrality. Specifically, I convert the rail network into a graph in which each track segment between two nodes is an edge weighted by its length in miles. For each segment, I calculate edge betweenness centralitye—that is, how many weighted shortest paths between all node pairs traverse that edge. Edges with low betweenness are inefficient, and therefore more likely to be abandoned.

The use of edge betweenness centrality is motivated by research on rail network analysis, showing that this measure is well suited for identifying the relative importance of network components (To 2015). The intuition is straightforward. Segments with high betweenness are critical bottlenecks that, if removed, would force traffic onto much longer alternative routes or risk disconnection; conversely, segments with low betweenness are less critical for connectivity and can therefore be abandoned with limited loss in performance. This captures the

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[19] A tempting instrument is simply the presence of abandoned rail lines; after all, every rail-trail begins with a corridor that first fell out of service. In principle, if abandonment were both strongly predictive of later trail conversion and uncorrelated with any other forces shaping housing markets and residential preferences, it would satisfy the conditions for a valid instrument. However, actual rail abandonment is not necessarily random. Actual abandonment patterns may reflect collapse of specific industries, shifts in freight technology, and patterns of urban decline. Those same forces can leave lingering impacts on neighborhood prices, incomes, and demographics at present. I do show results from the analysis using actual abandoned rail as an IV in Appendix C.

[20] Atack (2023) provides a spatial dataset of the historical rail network in 1911, but cross-referencing with the FRRandP abandoned rail data suggests it omits some abandoned lines that were active in the 1910s. Because my goal is to capture as many abandoned lines as possible in order to predict abandonment and eventual trail conversion, I construct my own historical rail network dataset.

[21] This approach would be problematic if rail were being built and abandoned at the same time, meaning that the network was changing. In practice, large-scale rail building (pre-1920s) did not overlap with large-scale rail abandonment (post 1980s), which lends credibility to my approach.

economic logic of rail contraction: as demand fell and maintenance costs rose, railroads shed redundant routes while preserving the core structure necessary to connect major origins and destinations. Figure 13 displays actual active and abandoned rail in Greater Boston alongside calculations of each segment's edge betweenness. Consistent with the aforementioned logic, I observe that actual abandoned rail tend to have low edge betweenness.

I calibrate the model by setting the retention fraction to 45% of the total length. That is, I flag "predicted abandoned" as the 45% of total rail mileage with the lowest betweenness. This choice aligns with observed U.S. rail decline, which is estimated to have been 254,000 miles at its peak to 140,000 miles today.

Figure 14 compares the rail segments predicted as abandoned by the algorithm with those actually abandoned, focusing on six metropolitan areas for visual clarity: Boston, New York, Atlanta, Chicago, Dallas, and Los Angeles. The maps illustrate that the algorithm captures many major abandonment corridors. In Boston, for example, it correctly predicts several prominent lines later converted into rail trails, including the Saugus Branch Railroad (now the Northern Strand Community Path), the Lexington and West Cambridge Railroad (now the Minuteman Bikeway), and portions of the Mass Central Railroad, which is currently being developed as the Mass Central Rail Trail.

Column 1 of Table 2 evaluates the prediction more formally by regressing actual abandoned rail presence on predicted abandoned rail presence within each census tract. My variable of interest is $\widehat{A}$, an indicator for predicted rail abandonment. I control for "Has Rail," equal to 1 if a tract contains any rail right-of-way (active or abandoned). This control accounts for the average difference between tracts with and without rail, so the coefficient on $\widehat{A}$ is identified by variation in predicted abandonment among rail tracts. I observe that predicted abandonment is strongly related to actual abandonment. Among rail tracts, those predicted to be abandoned are 45 percentage points more likely to contain an abandoned segment than other rail tracts. Independently, rail tracts not predicted to be abandoned are 29 percentage points more likely to contain an abandoned segment than tracts with no rail. Thus, moving from a tract with no rail to one with rail and predicted abandonment implies a 74 percentage point higher probability of actual abandonment.

Predicted abandoned rail presence should serve as an effective instrument if the following conditions hold: (1) it is positively correlated with trail presence (relevance), (2) it is effectively as-good-as-randomly distributed across census tracts (independence), (3) it cannot reduce the probability of trail creation once assigned (monotonicity), and (4) it influences housing and demographic outcomes only through its effect on trail creation (exclusion restriction).

In the next section, I present first-stage results to establish relevance. The instrument is constructed from historical rail nodes and geographic distance, using edge betweenness to predict which segments were most likely to be abandoned. Because this prediction is derived entirely from network geometry, it avoids legacy factors—such as industrial decline—that drove actual abandonment. This design makes predicted abandonment plausibly orthogonal to unobserved determinants of long-run neighborhood change, satisfying the independence condition. Monotonicity is also credible: if a segment is predicted to be abandoned, the effect should be non-negative—at worst, having no impact on trail creation, and at best raising the probability of conversion by increasing the likelihood that the line was actually abandoned.

The exclusion restriction requires that predicted abandonment affect housing and demographic outcomes only through its influence on trail creation. While this condition cannot be verified directly, the Greater Boston event study provides some supportive evidence. In the full sample estimates of rail trail impacts on housing value, housing supply, college educated share, and white share, shown in Figures A2, A3 , A5, and A7, respectively, the pre-trends in treatment groups are statistically indistinguishable from control group observations in the same year. Since rail trails pre-conversion are by definition abandoned rail, the flat pre-trends suggest that tracts with abandoned rail lines were not on distinct economic trajectories relative to tracts without such corridors.

For owner-occupancy—and, to a lesser extent, race—I do find some pre-period differences, making exclusion less secure for these outcomes. In the case of owner-occupancy, treated tracts were consistently 2–3 percentage points more owner-occupied throughout the pre-period, but the coefficients are flat, suggesting a persistent level gap rather than diverging pre-trends. For race, only one pre-period coefficient is statistically distinguishable from zero, providing little evidence of systematic pre-trends. I caution that these findings are drawn from Greater Boston, and the absence (or presence) of pre-trends in this setting may not generalize to the rest of the United States, where rail corridors and local political economies evolved differently.

Abstracting from the data, interviews with planners and stakeholders suggest that perceptions of abandoned corridors before conversion were mixed.[22] In many cases, nearby property owners viewed them as inconsequential "wild land." In others, they were seen as a buffer that provided privacy, or, conversely, as a nuisance if poorly maintained or associated with crime. This heterogeneity makes it unlikely that abandonment alone produced consistent, directional changes in neighborhood outcomes across tracts. For these reasons, I view exclusion as stronger for housing values, housing supply, and education, and income,

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[22] Interviews were conducted with the Massachusetts Department of Conservation & Recreation, Massachusetts Department of Transportation, and Rails-to-Trails Conservancy.

and weaker but still plausible for tenure and race. I treat predicted abandonment as my preferred instrument.

4.3 Empirical Strategy

Having established the logic of the instrument, I next turn to the estimation framework. Because precise trail opening dates are not consistently available nationwide, I adopt a long-differences specification that compares tract-level changes in outcomes between 1970 and 2020—the period when the vast majority of rail-to-trail conversions occurred. In this framework, any tract with a trail in 2020 is treated as having received a trail at some point between 1970 and 2020. The instrument constructed from predicted abandonment provides exogenous variation to predict which tracts gained a trail during this period, allowing me to recover causal estimates of the long-run cumulative effects of trail creation. I estimate the following system of equations:

$$\Delta Y_i = \pi_0 + \pi_1 \Delta \widehat{has\_trail}_i + \gamma' \mathbf{X}_i + \psi_{c(i)} + \epsilon_i \tag{2}$$

$$\Delta has\_trail_i = \alpha_0 + \alpha_1 \widehat{A_i} + \rho' \mathbf{X}_i + \psi_{c(i)} + \omega_i \tag{3}$$

where ΔY_i is the change in the outcome of interest (e.g., log median housing value) between 1970 and 2020 in tract i. The endogenous regressor Δhas_trail_i, is a binary change indicator equal to 1 if a rail trail appears in tract i between 1970 and 2020. I instrument Δhas_trail_i with $\widehat{A_i}$, an indicator for whether the tract contains a segment predicted to be abandoned by the network-based algorithm described above. The control vector $\mathbf{X}_i$ includes indicators for any rail presence, distance to the 1970 CBSA center, and baseline 1970 demographic and housing characteristics. All regressions include county fixed effects, and standard errors are Conley-adjusted with a 2-mile spatial cutoff. Income and housing values are expressed in 2020 dollars.

The long-differences framework focuses on changes rather than levels, eliminating any time-invariant tract characteristics (such as geography or longstanding land-use legacies) that might otherwise confound cross-sectional estimates. Although a small number of rail trails were established in the 1960s, only two are well documented: the Elroy–Sparta Trail and the Illinois Prairie Path. The former does not appear in the dataset because its location was not a census tract in 1970. Thus, I argue that, for all tracts that contain a rail trail, it is reasonable to assume that the trail was likely built between 1970 and 2020, so that $\Delta \widehat{has_trail}_i$ captures the relevant change in treatment status.

4.4 Results and Discussion

First-stage estimates in Table 2, Column 2, show that predicted abandoned rail presence is a strong and statistically significant predictor of trail development, with a high F-stat of 611, satisfying the relevance condition.

Tables 3 and 4 present two-stage least squares estimates using predicted abandonment as an instrument for trail creation. The magnitudes of the IV estimates are striking. Tracts that gained a rail trail between 1970 and 2020 experienced an 18 percent increase in median house values and a 14 percent increase in median household incomes relative to tracts without a trail, after controlling for any rail presence, county fixed effects and 1970s baseline characteristics. Housing supply also grew by 24 percent, suggesting that rail trails induced substantial new construction, rather than simply raising prices on a fixed housing stock.

On the demographic side, the presence of a trail is associated with a 5.3 percentage point increase in the college educated share, a 7.7 percentage point increase in the White share of the population, consistent with neighborhood compositional shifts. Owner occupancy did not meaningfully change. The IV magnitudes also align well with evidence from the Greater Boston event study. By the second decade after opening, Boston tracts with new trails saw 19 percent gains in values and 14 percent gains in incomes, very close to the national IV estimates.

The evidence suggests that rail trails transform neighborhoods across different geographies in the United States. These effects likely combine the direct value of the trails with the secondary changes they trigger, as the arrival of higher-income and educated residents amplifies neighborhood reinvestment and sorting over time (Couture & Handbury 2023, Couture et al. 2024). Incomes, education levels, and housing values all rise following trail conversion, consistent with both amenity capitalization and the in-migration of higher-income, college-educated, and White households.

The notable difference is the increase in housing supply observed nationally, in contrast to the negative supply response in Greater Boston. This pattern may reflect heterogeneity in how local housing markets adjust, depending on regional conditions. Alternatively, it may reflect potential reversals in longer-term trends.[23] The event study captures dynamic average treatment effects of rail trail openings, whereas the long-differences specification averages changes across pre- and post-periods, potentially smoothing out these dynamic adjustments. In Appendix D, I explore whether regional supply elasticity mechanisms drives housing supply responses.

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[23] Table A1 shows that in the event study, the $k = +3$ coefficient moves from an estimated -13% effect to approximately zero, suggesting some reversal. I omit this bin from the plots because it represents only a few observations, and it leads to extreme estimates for other outcomes.

Although the long-run coefficients may appear large, they are consistent with prior work on high-profile urban greenways. For instance, Black & Richards (2020) report residential housing price increases of up to 35 percent for units near the New York High Line, which exceeds the average 20 percent capitalization effect estimated here. That the average rail trail conversion produces effects on the same order of magnitude, albeit somewhat smaller, highlights the broader value of these projects across a diverse range of places. They demonstrate that the economic value of trails extends beyond celebrated flagship projects to the more ordinary corridors that make up the bulk of the U.S. rail trail network.

Taken together, I argue that rail trails appear to initiate cycles of economic renewal while reproducing familiar patterns of gentrification. The results depict rail trails as catalysts for neighborhood change—initiating economic revitalization but amplified through processes of sorting and reinvestment.

4.5 Comparison With OLS

As a baseline for comparison, I study how trails, active rail lines, and abandoned-but-unconverted corridors relate to neighborhood demographics. I employ naive ordinary least squares regressions that regress long run change in outcomes (1970 - 2020) on indicators for trail presence, active rail lines, and abandoned rail lines without trail.

These estimates provide an initial sense of how rail infrastructure is associated with my outcomes of interest and help establish a reference point for interpreting potential biases that the IV results may correct.

My estimation is as follows:

$$\Delta Y_i = \beta_0 + \beta_1 Has\_Trail_i + \beta_2 Has\_Active_i + \beta_3 Has\_Abandoned\_NoTrail_i + \gamma \mathbf{X}_i + \delta_{c(i)} + \varepsilon_i \quad (4)$$

where Y_i represents the change in the outcome of interest between 1970 and 2020 (e.g. 2020 log median housing value - 1970 log median housing value) in census tract i, Has_Trail_i is an indicator for whether tract i contains a rail trail, Has_Active_i and $Has\_Abandoned\_NoTrail_i$ are indicators for the presence of active rail and abandoned rail with no trail conversion, respectively. $\mathbf{X}_i$ is a vector of census and geographical controls, and $\delta_{c(i)}$ represents a county fixed effect designed to account for unobserved heterogeneity across local areas. For ease of interpretation, I exclude tracts that have both active rail and abandoned rail, or active rail and trail. I use Conley spatial standard errors with a 2 mile spatial cutoff. All monetary outcomes are recorded in 2020 real dollars.

Because the dependent variable is a long difference, the estimates absorb any time-invariant tract characteristics (soil quality, distance to CBD, historic industrial land use, etc.). The coefficients β_1, β_2, and β_3 therefore summarize how much more (or less) a tract's outcomes changed from 1970 to 2020 if, by 2020, it has a trail, an active rail line, or an abandoned-but-unconverted corridor, relative to tracts with no corridor (conditioning on controls and county fixed effects).

Note that these estimates are not causal, because corridor status is measured at the end of the period and is endogenous: places on different trajectories were more or less likely to build a trail or retain/abandon rail, and other time-varying unobservables (policy changes, rezoning, local investments) may move both corridor status and outcomes. Thus, the OLS results serve as a descriptive benchmark. They describe how the long-run trajectories of tracts that ended up with trails, active rail, or abandoned corridors differ from those of tracts without corridor exposure.

Tables 5 and 6 report associations between corridor types and long-run changes (1970–2020) in neighborhood outcomes. Tracts that end up with a trail exhibit larger gains across several outcomes: median house values rise by 7% (Tables 5 Column 1), and the housing stock by 16% (Tables 5 Column 2). There does not appear to be a difference in the change in owner-occupancy, as tracts with trails are imprecisely estimated to have 0.2 percentage point more owner-occupancy relative to control tracts (Tables 5 Column 3). On demographics, trails are associated with a 2.9 percentage point increase in college educated share, 5% increase in median household income (Table 6 Column 1) and a 3.4 percentage point increase in the White share (Table 6, Column 2) Taken at face value, places that ultimately built trails experienced faster value and income growth and expanded housing supply relative to tracts without corridors.

Active rail is linked to modestly lower house-value growth (-2%) and a small decline in owner-occupancy (–0.55 percentage point), consistent with noise/traffic disamenities. At the same time, housing supply increases by about 6%, suggesting densification near rail lines. Places near active rails seem to have a small decrease in share college educated (5 percentage points, significant at 10% confidence). Income and racial composition changes are small and statistically imprecise.

Interestingly, abandoned-only tracts also show higher house-value growth (2.8%) and a 3% increase in housing units. These associations indicate that unconverted corridors are not uniformly indistinguishable from places with no trail; some are located in places that also saw meaningful neighborhood change.

Across all outcomes, the IV estimates are substantially larger than the corresponding OLS results, suggesting that OLS underestimates the causal effect of trail openings. This pattern is consistent with negative selection into trail development: corridors that were ultimately converted to trails often ran through areas with weaker economic legacies, such that simple correlations understate the benefits of conversion.

4.6 Robustness Check

As a robustness check, I estimate reduced-form regressions of the impact of predicted rail abandonment on changes in outcomes from 1970 to 1980. The goal of this exercise is to test whether the instrument itself affects neighborhood outcomes in the absence of rail-trail conversions. Ideally, I would use an earlier pre-period that fully predates the development of rail trails but still includes rail abandonment. However, I am limited by the availability of harmonized census panel data, which begins in 1970.[24]

As a next-best approach, I regress 1970–1980 changes in outcomes on predicted abandonment, controlling for the presence of any rail (abandoned and active) and the same baseline covariates used in the main IV specifications. Because most rail trails were constructed after the 1980s, this period captures a time when abandoned rail lines existed but trail conversions were rare. Significant coefficients of the instrument on 1970–1980 outcome changes would likely pick up any correlations between predicted abandonment and other factors affecting neighborhood trends outside the trail channel, such as the direct effect of rail abandonment. This would potentially weaken the exclusion restriction. I estimate the following regression:

$$\Delta Y_i = \beta_0 + \beta_1 \Delta\widehat{A_i} + \gamma' \mathbf{X}_i + \psi_{c(i)} + \epsilon_i \tag{5}$$

where ΔY_i is the change in the outcome of interest (e.g., log median housing value) between 1970 and 1980 in tract i, the control vector $\mathbf{X}_i$ includes indicators for any rail presence, distance to the 1970 CBSA center, and baseline 1970 demographic and housing characteristics. All regressions include county fixed effects, and standard errors are Conley-adjusted with a 2-mile spatial cutoff. Income and housing values are expressed in 2020 dollars.

Tables 7 and 8 present the results. I observe that across the board, predicted abandonment shows very small pre-period associations with 1970–1980 outcome changes. Given the large sample, some coefficients register as significant, but magnitudes are an order of magnitude smaller than post-1980 effects. This pattern is broadly consistent with the instrument not violating exclusion restriction. It cannot entirely rule out a little early trail activity or correlated corridor dynamics in the 1970s, but any such influence appears minor. Overall, these placebo tests support the validity of the instrument.

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[24] Extending further back would also require coarser geographic units, obscuring the hyperlocal effects of rail-trail development.

5 Conclusion

This paper estimates the causal impact of rail trail development on neighborhood change. Rail trails represent a rapidly expanding form of public infrastructure, with substantial potential for growth given the extensive legacy of disused rail corridors. Understanding how they reshape neighborhoods is therefore central to contemporary policy discussions.

I begin with an event study of Greater Boston, which shows that trails are quickly capitalized into housing markets and continue to influence neighborhood trajectories over subsequent decades. Trail openings spark immediate increases in housing values and attract more educated, higher-income residents, which appears to further increase demand and amplify price growth over time. At the national level, I use a long-differences instrumental variables framework, predicting rail abandonment through a connectivity-based measure of network efficiency. The IV estimates are striking: tracts that gained a trail between 1970 and 2020 experienced roughly 20 percent higher growth in housing values, accompanied by similar patterns of sorting. Unlike Boston, however, housing supply expanded on average, suggesting that trails can stimulate new development where supply constraints are less binding.

These findings situate rail trails within the broader literature on neighborhood revitalization, which emphasizes how new amenities raise property values, attract investment, and bolster municipal tax bases, but often at the cost of affordability pressures and demographic change (Rosenthal & Ross 2015). From a policy perspective, this raises the question: should we build more rail trails? Evidence from Vigdor (2010) suggests that the price increases associated with revitalization are typically smaller than households' willingness to pay for neighborhood improvements. Although I do not estimate welfare gains directly, future research could examine this dimension.

At the same time, distributional consequences remain uncertain. Homeowners who sell benefit from capital gains, while renters and future residents face higher costs. Future work could explore heterogeneity by initial neighborhood composition to identify who benefits and who bears the costs, as well as the mechanisms underlying trail value—whether through recreation, complementary retail and service activity, or transportation alternatives. Environmental impacts, such as reduced vehicle miles traveled or lower emissions, also warrant study.

Overall, the findings highlight the potential of rail trails to drive meaningful neighborhood change. Their effects on prices, income, housing supply, and demographics suggest that they are strongly—though heterogeneously— valued by households and capable of reshaping the long-run economic and social trajectories of the communities they traverse.

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6 Figures and Tables

6.1 Figures

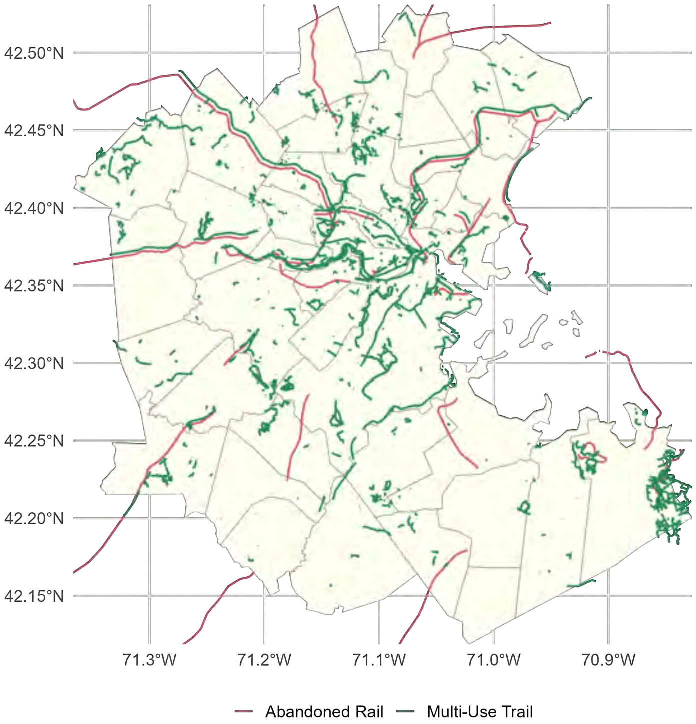
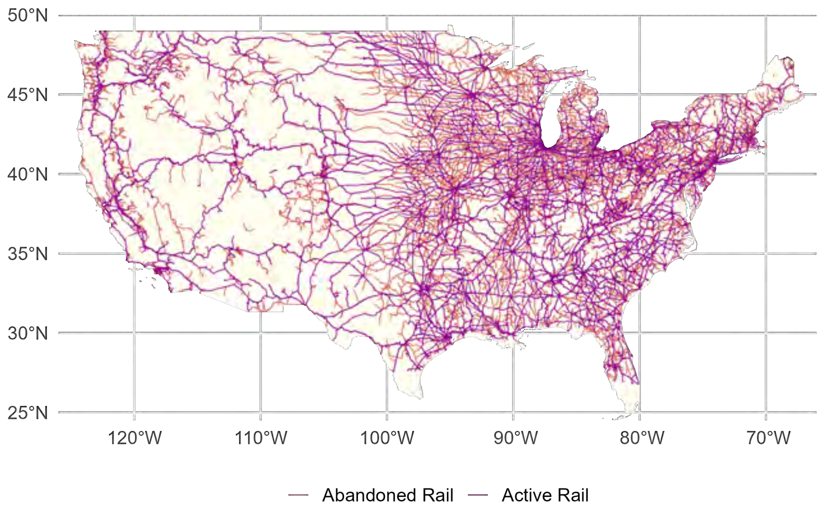
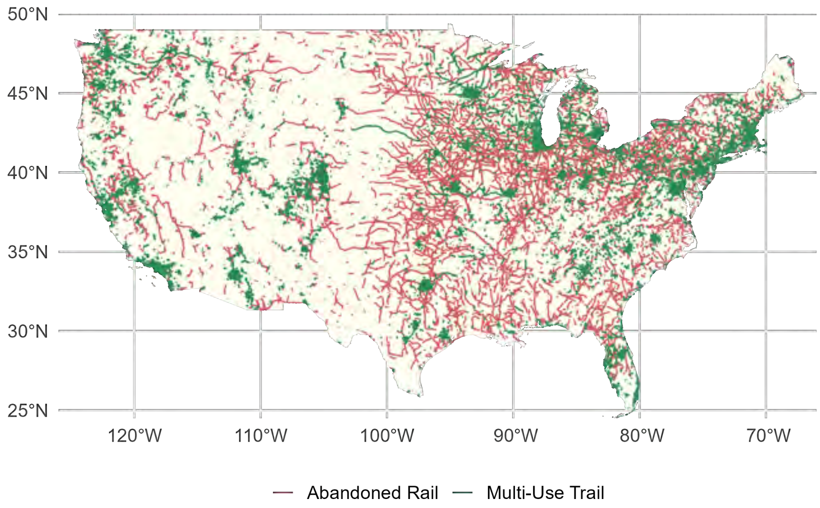


Figure 1: Abandoned Rail and Multi-use Trail in Greater Boston

Note: This figure shows the distribution of active and abandoned rail lines and multi-use trails in the Greater Boston Area. For clarity, multi-use trail data has been slightly offset to distinguish overlapping rail and trail lines.



(a) Abandoned and Active Rail



(b) Abandoned Rail and Bike Trail

Figure 2: Distribution of Rail Lines and Trails in the United States

Note: This figure shows the distribution of active and abandoned rail lines and multi-use trails across the contiguous United States. Panel (a) shows active and abandoned rail lines. Panel (b) shows abandoned rail lines and overlaid with multi-use trails.

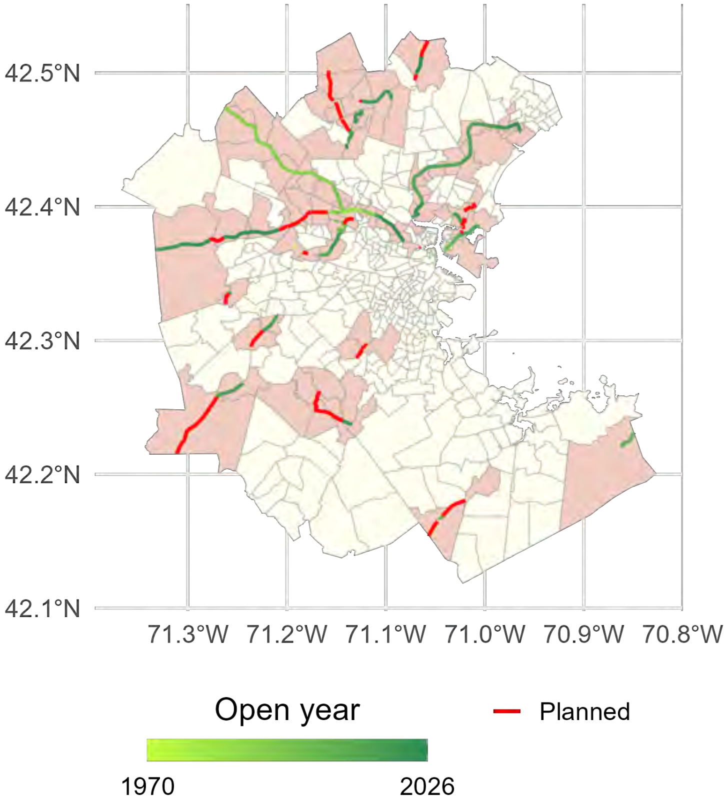


Figure 3: Greater Boston Rail Trails

Note: This figure shows rail planned and existing rail trails the Greater Boston area. Boundaries represent census tracts. In my main event study analysis, I restrict the comparison to tracts containing existing or planned trails— highlighted in pink. I define Greater Boston as comprising of the following municipalities: Randolph, Stoneham, Winchester, Chelsea, Weymouth, Norwood, Somerville, Milton, Saugus, Watertown, Canton, Wakefield, Revere, Waltham, Woburn, Newton, Arlington, Belmont, Cambridge, Lincoln, Medford, Melrose, Boston, Needham, Dover, Westwood, Lexington, Braintree, Quincy, Wellesley, Holbrook, Weston, Hingham, Everett, Brookline, Malden, Lynn, and Dedham. Data is from MassDOT.

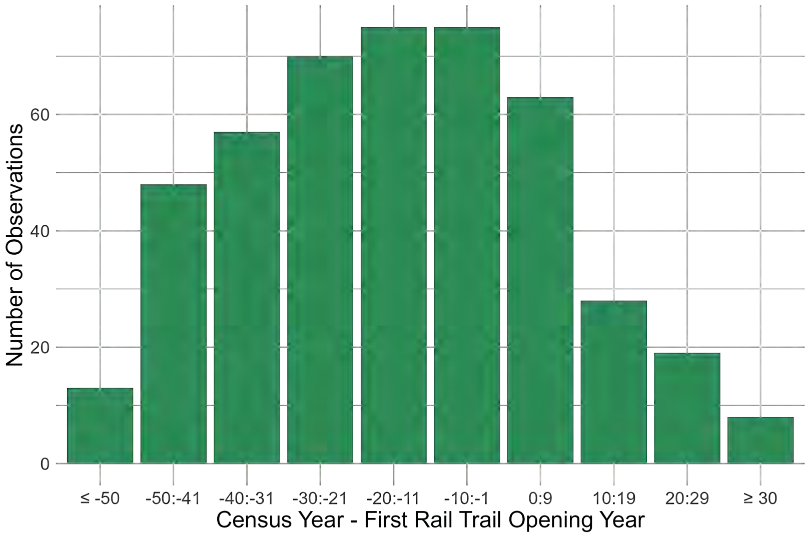


Figure 4: Distribution of Event Times (1970–2020 Panel, 1970-Harmonized Tracts)

Note: This figure shows the distribution of event times from combining rail trail segment opening dates with a panel dataset from 1970 to 2020, harmonized to 1970 boundaries. Event time is defined as the difference between the Census year and the corresponding trail opening year. Since the census is conducted every ten years, I then group my event time into decade bins.

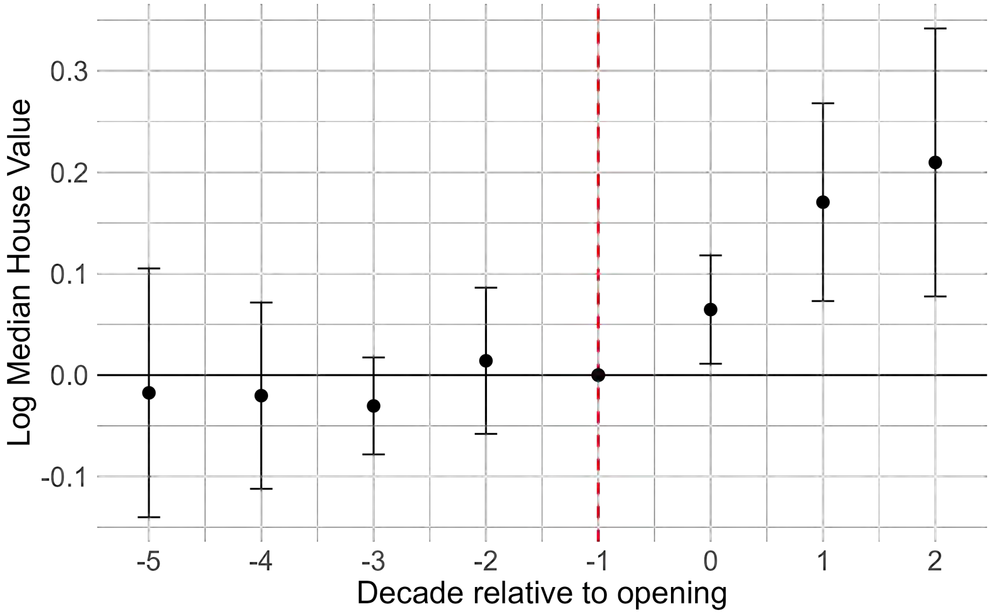


Figure 5: Event Study: Rail Trail Effects on Log Median Housing Value (Corridor Sample)

Note: Event study estimates for Greater Boston region, restricted to tracts located along existing or planned rail trail corridors. Census tract characteristics are observed every ten years. Decade 0 represents 0-9 years after opening, and subsequent decades are defined analogously. Estimated coefficients are relative to the decade prior to trail opening (baseline). Standard errors are Conley-adjusted with a two-mile spatial cutoff.

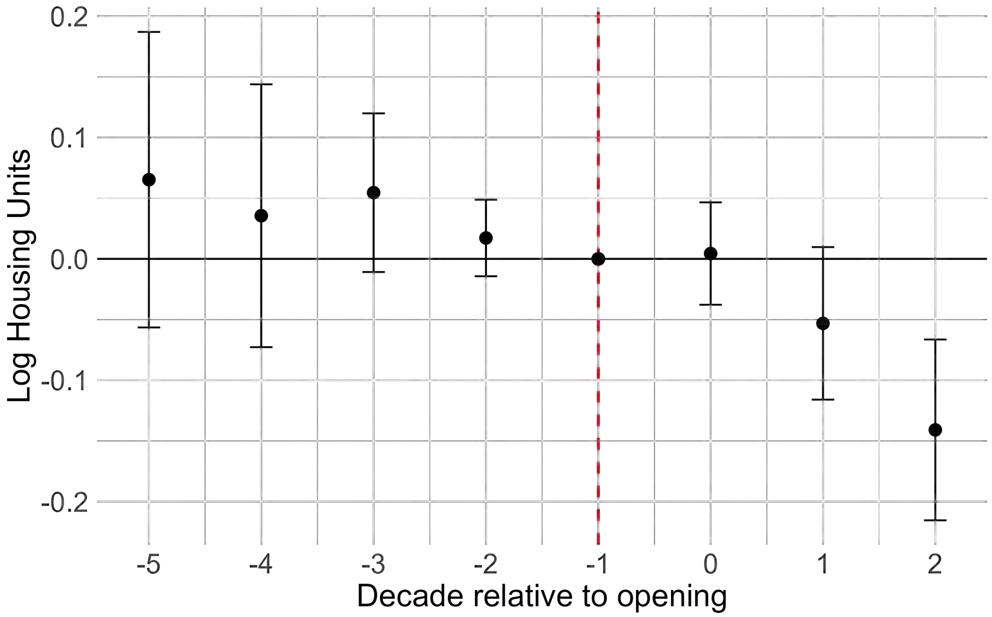


Figure 6: Event Study: Rail Trail Effects on Log Number of Housing Units (Corridor Sample)

Note: Event study estimates for Greater Boston region, restricted to tracts located along existing or planned rail trail corridors. Census tract characteristics are observed every ten years. Decade 0 represents 0-9 years after opening, and subsequent decades are defined analogously. Estimated coefficients are relative to the decade prior to trail opening (baseline). Standard errors are Conley-adjusted with a two-mile spatial cutoff.

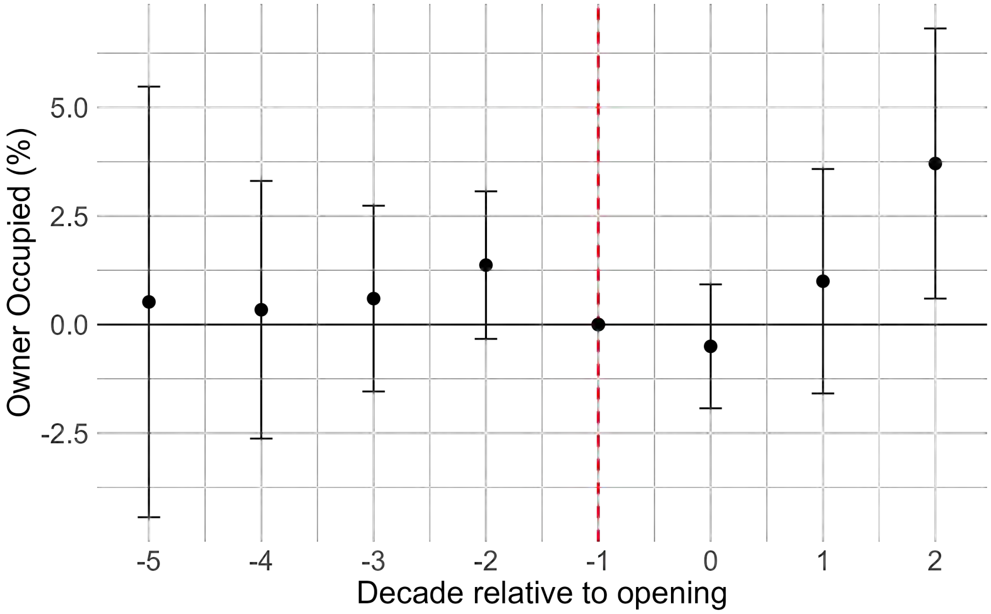


Figure 7: Event Study: Rail Trail Effects on Share of Owner-Occupied Housing (Corridor Sample)

Note: Event study estimates for Greater Boston region, restricted to tracts located along existing or planned rail trail corridors. Census tract characteristics are observed every ten years. Decade 0 represents 0-9 years after opening, and subsequent decades are defined analogously. Estimated coefficients are relative to the decade prior to trail opening (baseline). Standard errors are Conley-adjusted with a two-mile spatial cutoff.

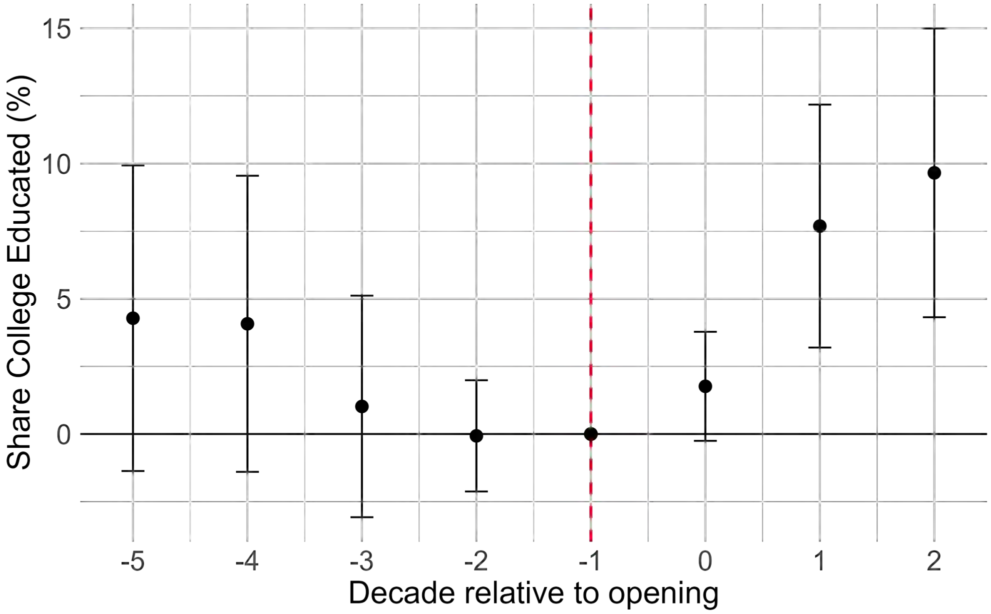


Figure 8: Event Study: Rail Trail Effects on College Educated Share of Population (Corridor Sample)

Note: Event study estimates for Greater Boston region, restricted to tracts located along existing or planned rail trail corridors. Census tract characteristics are observed every ten years. Decade 0 represents 0-9 years after opening, and subsequent decades are defined analogously. Estimated coefficients are relative to the decade prior to trail opening (baseline). Standard errors are Conley-adjusted with a two-mile spatial cutoff.

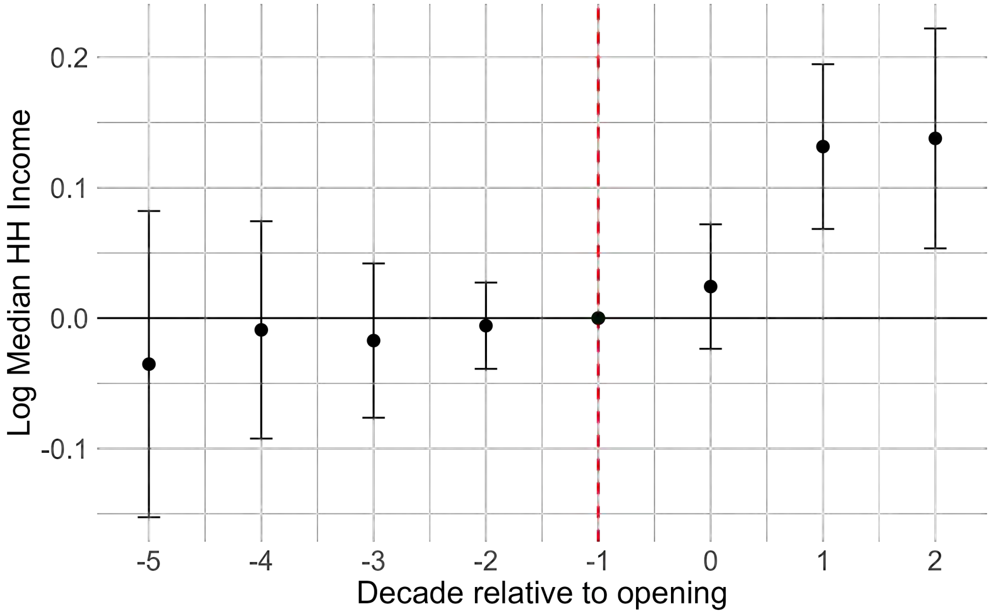


Figure 9: Event Study: Rail Trail Effects on Log Median Household Income (Corridor Sample)

Note: Event study estimates for Greater Boston region, restricted to tracts located along existing or planned rail trail corridors. Census tract characteristics are observed every ten years. Decade 0 represents 0-9 years after opening, and subsequent decades are defined analogously. Estimated coefficients are relative to the decade prior to trail opening (baseline). Standard errors are Conley-adjusted with a two-mile spatial cutoff.

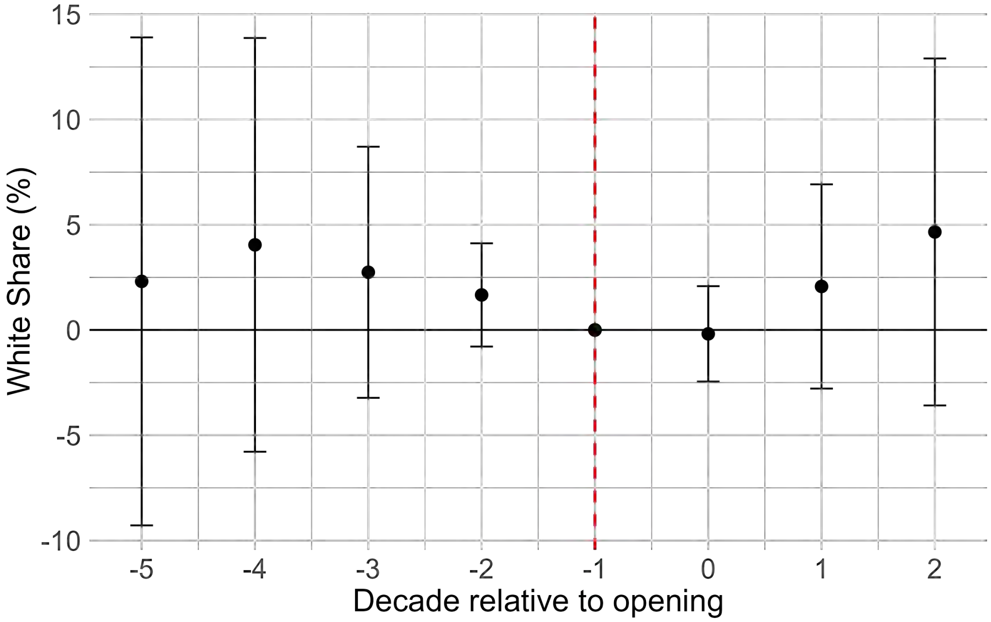


Figure 10: Event Study: Rail Trail Effects on White Share of Population (Corridor Sample)

Note: Event study estimates for Greater Boston region, restricted to tracts located along existing or planned rail trail corridors. Census tract characteristics are observed every ten years. Decade 0 represents 0-9 years after opening, and subsequent decades are defined analogously. Estimated coefficients are relative to the decade prior to trail opening (baseline). Standard errors are Conley-adjusted with a two-mile spatial cutoff.

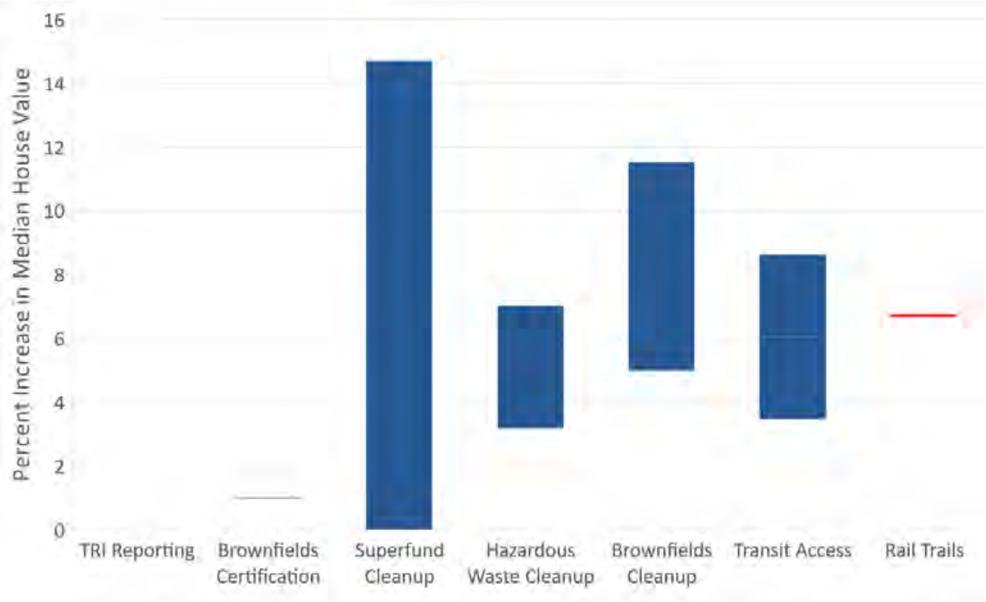


Figure 11: Capitalization of Other Public Amenities into Housing Values

Note: Estimates are taken from Bui & Mayer (2003) (TRI reporting), Linn (2013) (brownfields certification), Greenstone & Gallagher (2008), Gamper-Rabindran & Timmins (2013) (Superfund cleanup), Cassidy et al. (2022), Guignet & Nolte (2024) (hazardous waste cleanup), Haninger et al. (2017) (brownfields cleanup), and Bowes & Ihlanfeldt (2001), Diao et al. (2017) (transit access).

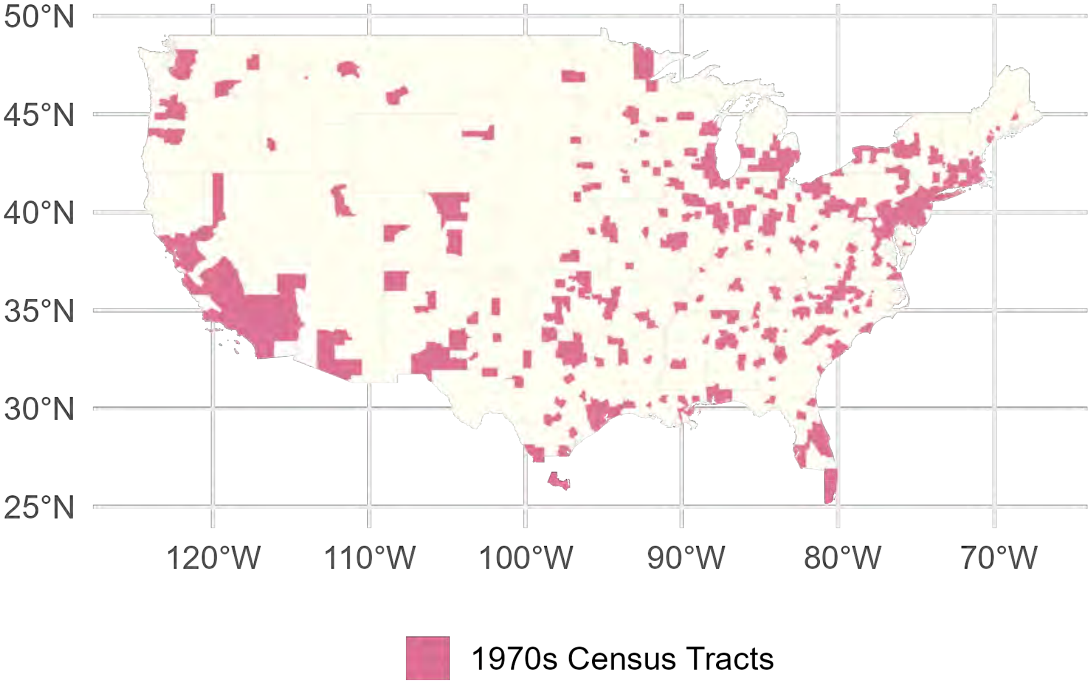
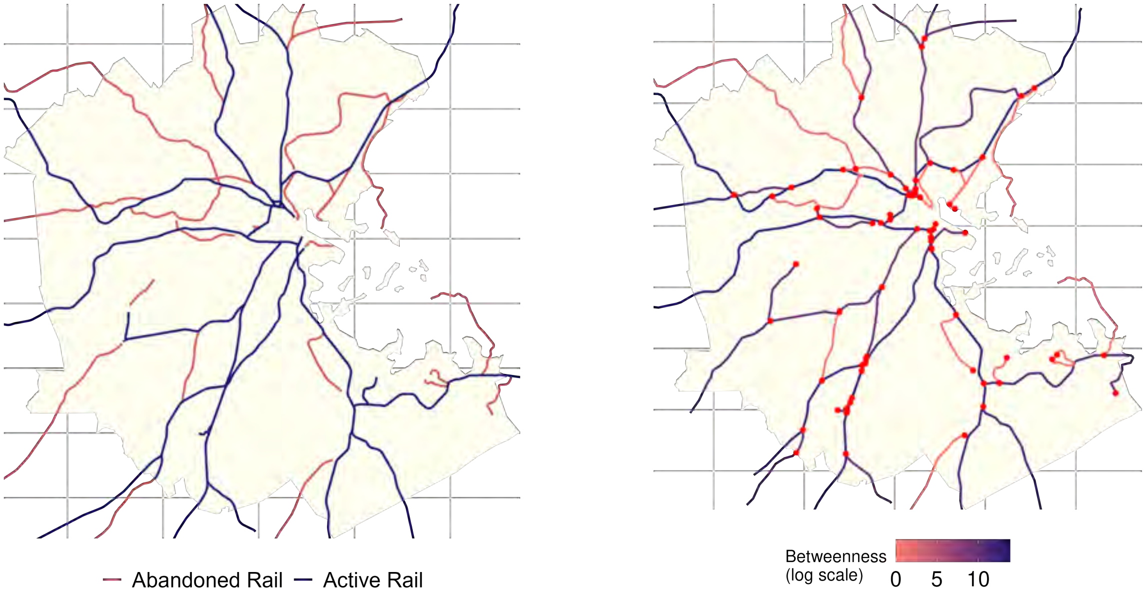


Figure 12: Geographic Scope for National Empirical Analysis

Note: This figure illustrates the areas included in my nationwide empirical analysis, using 1970 census tract boundaries. Due to the smaller U.S. population in earlier decades, this dataset does not cover the entire country, but includes include the largest cities and selected surrounding areas.

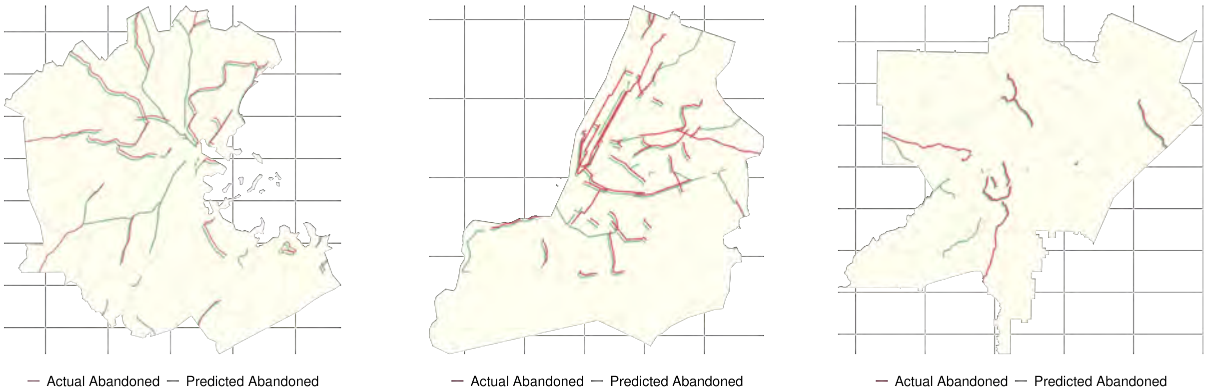


(a) Abandoned and Active Rail

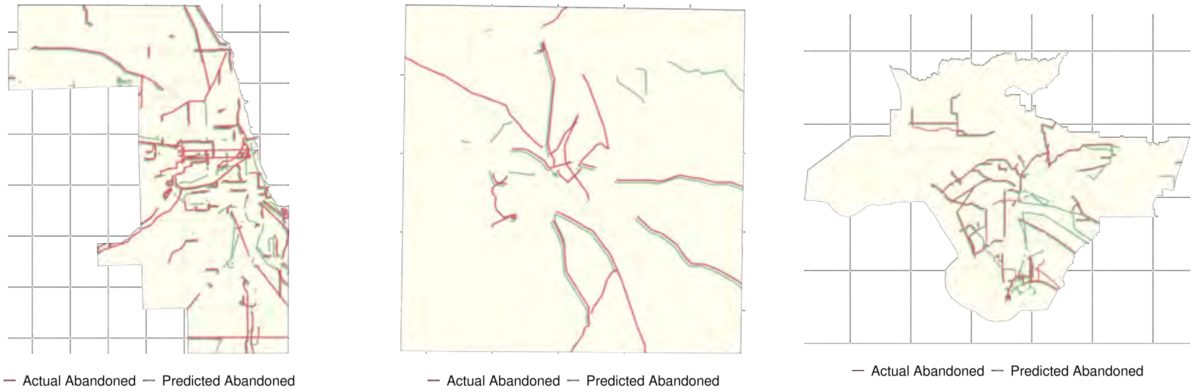
(b) Edge Betweenness

Figure 13: Active and Abandoned Rail vs Edge Betweeness in Greater Boston

Note: This figure illustrates the use of edge betweenness centrality in predicting rail abandonment, using Greater Boston as an example. Nodes are identified based on rail crossings and endpoints, marked by red circles. Edges are segments between two nodes. An effective prediction would mean that abandoned rail in the historical rail network are also segments with low edge betweenness.



(a) Boston (b) New York (c) Atlanta



(d) Chicago (e) Dallas (f) Los Angeles

Figure 14: Rail Abandonment Predicted by Betweenness Centrality: Six Metropolitan Areas

Note: This figure shows the betweenness-centrality prediction of rail abandonment, zoomed in on six example metropolitan for visual clarity. Green lines indicate segments predicted to be abandoned based on the betweenness-centrality algorithm, which ranks segments by their contribution to overall network connectivity and classifies the bottom 50% as abandoned; red lines are actually abandoned segments. Where green and red coincide, the prediction is correct. Green-only segments are false positives (active lines predicted as abandoned). Red-only segments are false negatives (abandoned lines the model predicted as active). For clarity, actual abandoned rail data are slightly offset to distinguish overlapping predicted and actual abandoned rail lines.

6.2 Tables

Table 1: Greater Boston Rail Trail Segments by Opening Date

Name	Year Open	Towns	N Tracts
Alewife Linear Park Trail	1985	Somerville, Cambridge	3
Bay Colony Rail Trail	2016	Needham	1
Chelsea Greenway	2018	Chelsea	2
Community Path of Lynn	2021	Lynn	3
Dedham Rail Trail	2019	Dedham, Boston	3
East Boston Greenway	2002	Boston	4
East Boston Greenway	2007	Boston	3
East Boston Greenway	2014	Boston	2
Encore Resort Path	2019	Everett, Boston	2
Fitchburg Cutoff	1990	Belmont	1
Fresh Pond Paths	2002	Cambridge	1
Linear Park	1970	Watertown	1
Mass Central Rail Trail	2019	Weston	2
Mass Central Rail Trail	2024	Waltham	4
Minuteman Commuter Bikeway	1993	Arlington, Lexington	8
Minuteman Commuter Bikeway	1998	Arlington	2
Newton Lower Falls Branch	2012	Newton	1
Northern Strand Community Trail	2012	Malden, Everett	7
Northern Strand Community Trail	2015	Saugus, Revere	3
Northern Strand Community Trail	2021	Lynn	2
Randolph Rail Trail	2005	Randolph	1
Somerville Community Path	1985	Somerville, Cambridge	3
Somerville Community Path	1995	Somerville	3
Somerville Community Path	2008	Somerville	1
Somerville Community Path	2015	Somerville	1
Somerville Community Path	2023	Somerville	3
Tri-Community Greenway	2019	Woburn, Stoneham, Winchester	8
Upper Falls Greenway	2015	Newton	1
Wakefield-Lynnfield Rail Trail	2026	Wakefield	2
Watertown Greenway	2011	Watertown	2
Whitney Spur Rail Trail	2007	Hingham	1

Note: This table lists the rail trail segments considered in the Greater Boston event study analysis. Each row corresponds to a trail segment that is the *first* rail trail to open within the census tract(s) it intersects, and thus marks the onset of treatment in the event study. For reference, the towns through which each segment passes are included. The final column indicates the number of tracts for which the segment marks the first trail opening. Rail trails that opened in multiple phases appear in multiple rows with different years.

Table 2: Predictions of Instrument on Actual Abandoned Rail and Trail Presence

	Dependent variable:	
	Has Abandoned	Has Trail
	(1)	(2)
$\widehat{A}$	0.450***	0.184***
	(0.009)	(0.007)
Has Any Rail	0.287***	0.117***
	(0.009)	(0.006)
Location FE	County	County
Geography & 1970 Baseline Controls	yes	yes
F-stat	-	611
Observations	32,628	32,628
Adjusted R^2	0.563	0.250

Note: This table reports two regressions using predicted rail abandonment, $\widehat{A}$. Column (1) validates the prediction by regressing an indicator for actual abandoned rail on $\widehat{A}$. Column (2) presents the first-stage regression, with actual trail presence as the dependent variable. Both specifications include a control for "Has Any Rail," equal to 1 if a tract intersects any rail right-of-way (active or abandoned), which nets out the broader difference between rail and non-rail tracts. All models include county fixed effects, geography controls (distance to the urban center and land area), and 1970 baseline covariates (selected via LASSO). Standard errors are Conley-adjusted with a two-mile spatial cutoff.

Sample: 1970 census tracts. Share of tracts with abandoned rail = 37%; share with a trail = 12%.

*p<0.1; **p<0.05; ***p<0.01.

Table 3: IV Estimates of Trail Presence on Housing Changes

	Dependent variable:		
	Δ Log Median House Value	Δ Log Housing Supply	Δ Share Owner Occupied (%)
	(1)	(2)	(3)
Δ Has Trail (Predicted)	0.169***	0.212***	1.465
	(0.039)	(0.049)	(0.978)
Location FE	County	County	County
Has Any Rail	yes	yes	yes
Geography & 1970 Baseline Controls	yes	yes	yes
Interpretation:	+18%	+24%	+1.5 pp
Mean Outcome	$195,303	1,427	-7%
Observations	32,120	32,623	32,623
Adjusted R^2	0.687	0.567	0.439

Note: This table presents two-stage least squares estimates of the relationship between trail presence and housing outcomes. The endogenous variable is the change in "Δ Has Trail," an indicator for whether a given 1970 census tract area contains a trail. The instrument is whether the tract contains a historical rail that is predicted to have been abandoned at the present.

Geography Controls: active rail, distance from urban center, land area

1970 Baseline Controls (selected via LASSO): log median house value, log median rent, housing supply, share single family housing, share multi-family housing, share new housing stock, share owner occupied housing, log median household income, share white, population, share high school educated, share college educated, share foreign born, commute type, industry

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: IV Estimates of Trail Presence on Demographic Changes

	Dependent variable:		
	Δ Share College Educated (%)	Δ Log Median HH Income	Δ Share White (%)
	(1)	(2)	(3)
Δ Has Trail (Predicted)	5.298^{***}	0.134^{***}	7.735^{***}
	(1.289)	(0.031)	(1.964)
Location FE	County	County	County
Has Any Rail	yes	yes	yes
Geography & 1970 Baseline Controls	yes	yes	yes
Interpretation:	+5.3 pp	+14%	+7.7 pp
Mean Outcome	29%	$9,685	-32%
Observations	32,625	32,486	32,628
Adjusted R^2	0.344	0.570	0.590

Note: This table presents two-stage least squares estimates of the relationship between trail presence and housing outcomes. The endogenous variable is the change in "Δ Has Trail," an indicator for whether a given 1970 census tract area contains a trail. The instrument is whether the tract contains a historical rail that is predicted to have been abandoned at the present.

Geography Controls: active rail, distance from urban center, land area

1970 Baseline Controls (selected via LASSO): log median house value, log median rent, housing supply, share single family housing, share multi-family housing, share new housing stock, share owner occupied housing, log median household income, share white, population, share high school educated, share college educated, share foreign born, commute type, industry

${}^{*}p < 0.10$, ${}^{**}p < 0.05$, ${}^{***}p < 0.01$.

Table 5: OLS Estimates of Rail and Trail Presence on Housing Changes

	Dependent variable:		
	Δ Log Median House Value	Δ Log Housing Supply	Δ Share Owner Occupied (%)
	(1)	(2)	(3)
Has Trail	0.072^{***}	0.146^{***}	-0.213
	(0.011)	(0.015)	(0.319)
Has Active Rail	-0.023^{***}	0.060^{***}	-0.552^{***}
	(0.009)	(0.010)	(0.198)
Has Abandoned (No Trail)	0.028^{**}	0.031^{***}	0.304
	(0.011)	(0.012)	(0.258)
Location FE	County	County	County
Geography & 1970 Baseline Controls	yes	yes	yes
Mean Outcome	$195,303	1,427	-7%
Observations	26,080	26,490	26,490
Adjusted R^2	0.699	0.568	0.456

Geography Controls: distance from urban center, land area.
1970 Baseline Controls (selected via LASSO): population, number of housing units, median housing value, share owner occupied housing, share new housing, commute type, industry type, share high school educated, share college educated, share white, share foreign born.
Sample excludes tracts with overlapping active rail and trail or active rail and abandoned lines.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 6: OLS Estimates of Rail and Trail Presence on Population Changes

	Dependent variable:		
	Δ Share College (%)	Δ Log Median HH Income	Δ Share White (%)
	(1)	(2)	(3)
Has Trail	2.932^{***}	0.046^{***}	3.404^{***}
	(0.413)	(0.010)	(0.570)
Has Active Rail	-0.512^{*}	-0.007	-0.038
	(0.301)	(0.007)	(0.432)
Has Abandoned (No Trail)	0.662	0.019^{*}	0.923
	(0.421)	(0.010)	(0.568)
Location FE	County	County	County
Geography & 1970 Baseline Controls	yes	yes	yes
Mean Outcome	29%	$9,685	-32%
Observations	26,491	26,381	26,493
Adjusted R^2	0.348	0.574	0.585

Geography Controls: distance from urban center, land area.
1970 Baseline Controls (selected via LASSO): population, number of housing units, median housing value, share owner occupied housing, share new housing, commute type, industry type, share high school educated, share college educated, share white, share foreign born.
Sample excludes tracts with overlapping active rail and trail or active rail and abandoned lines.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 7: Placebo Test: Predicted Abandonment and 1970 Housing Outcomes

	Dependent variable:		
	Δ Log Median House Value	Δ Log Housing Supply	Δ Share Owner Occupied (%)
	(1)	(2)	(3)
Has Predicted Abandoned	0.010^{***}	0.010	-0.159
	(0.003)	(0.009)	(0.196)
Has Any Rail	-0.005	-0.006	-0.600^{***}
	(0.004)	(0.009)	(0.196)
Location FE	County	County	County
Geography & 1970 Baseline Controls	yes	yes	yes
Mean Outcome	$38,422	327	-4%
Observations	31,531	32,613	32,613
Adjusted R^2	0.647	0.168	0.120

Note: Placebo regressions of 1970 to 1980 change in housing outcomes on predicted abandonment. Because few trails were built in this period, significant coefficients would indicate that the instrument is correlated with factors that directly impact neighborhood trends other than trail conversion.
Geography Controls: active rail, distance from urban center, land area
1970 Baseline Controls (selected via LASSO): share single family housing, share multi-family housing, share new housing stock, population, share high school educated, share college educated, share foreign born, commute type, industry
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8: Placebo Test: Predicted Abandonment and 1970 Demographic Outcomes

	Dependent variable:		
	Δ Share College (%)	Δ Log Median HH Income	Δ Share White (%)
	(1)	(2)	(3)
Has Predicted Abandoned	0.162^{**}	0.007^{***}	0.560^{**}
	(0.081)	(0.002)	(0.238)
Has Any Rail	-0.051	-0.008^{***}	-0.134
	(0.093)	(0.003)	(0.276)
Location FE	County	County	County
Geography & 1970 Baseline Controls	yes	yes	yes
Mean Outcome	5%	$-3,461	-8%
Observations	31,838	31,770	32,628
Adjusted R^2	0.240	0.677	0.294

Note: Placebo regressions of 1970 to 1980 change in demographic outcomes on predicted abandonment. Because few trails were built in this period, significant coefficients would indicate that the instrument is correlated with factors that directly impact neighborhood trends other than trail conversion.
Geography Controls: active rail, distance from urban center, land area
1970 Baseline Controls (selected via LASSO): share single family housing, share multi-family housing, share new housing stock, population, share high school educated, share college educated, share foreign born, commute type, industry
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix A Additional Tables and Figures

A.1 Figures

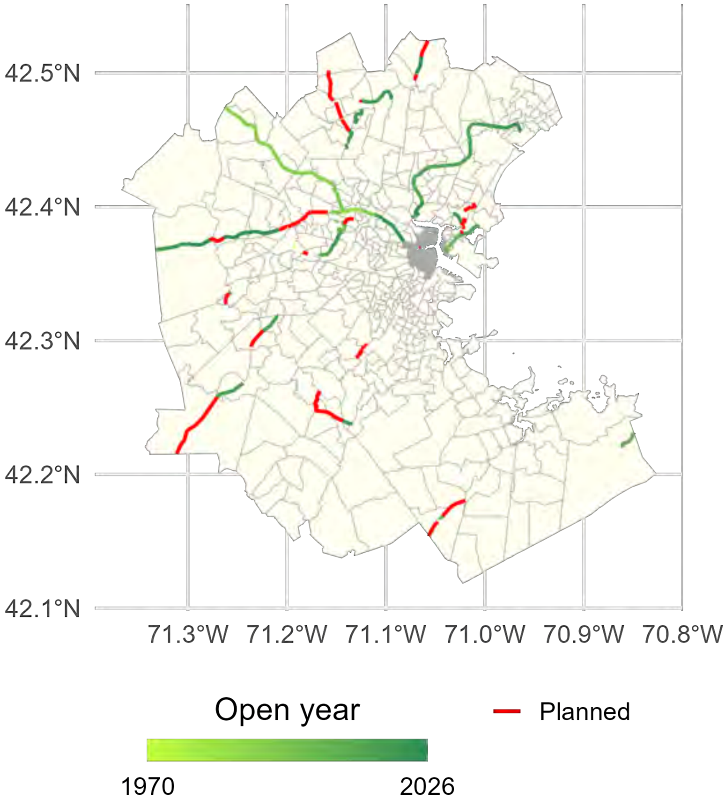


Figure A1: Greater Boston Rail Trails and Census Tracts Used in the Full-Sample Event Study)

Note: This figure maps the broader sample of census tracts used in the alternative event study, which includes the majority of tracts in the region, not only those along abandoned rail corridors. Tracts within one mile of the city center (shown in gray) are excluded. Boundaries represent census tracts. I define Greater Boston as comprising of the following municipalities: Randolph, Stoneham, Winchester, Chelsea, Weymouth, Norwood, Somerville, Milton, Saugus, Watertown, Canton, Wakefield, Revere, Waltham, Woburn, Newton, Arlington, Belmont, Cambridge, Lincoln, Medford, Melrose, Boston, Needham, Dover, Westwood, Lexington, Braintree, Quincy, Wellesley, Holbrook, Weston, Hingham, Everett, Brookline, Malden, Lynn, and Dedham. Data is from MassDOT.

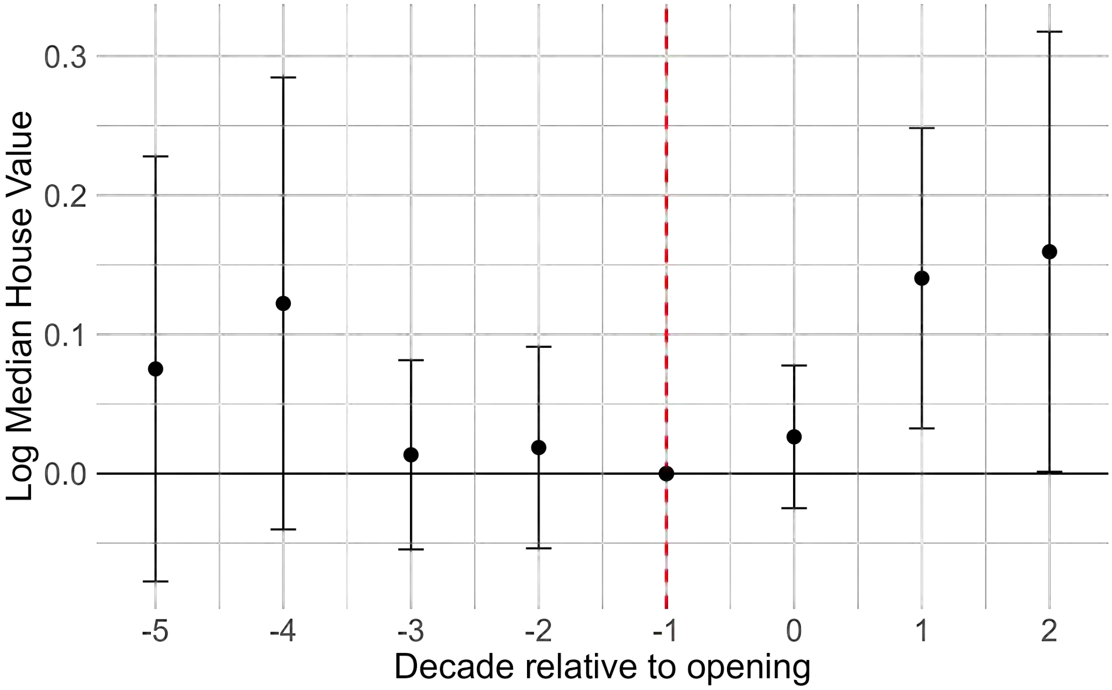


Figure A2: Event Study: Rail Trail Effects on Log Median Housing Value (Full Sample)

Note: Event study estimates for Greater Boston region, excluding tracts within 2 miles of the city center, which may have a distinct development trajectory. Estimated coefficients are relative to the decade prior to trail opening (baseline). Census tract characteristics are observed every ten years. Standard errors are Conley-adjusted with a two-mile spatial cutoff.

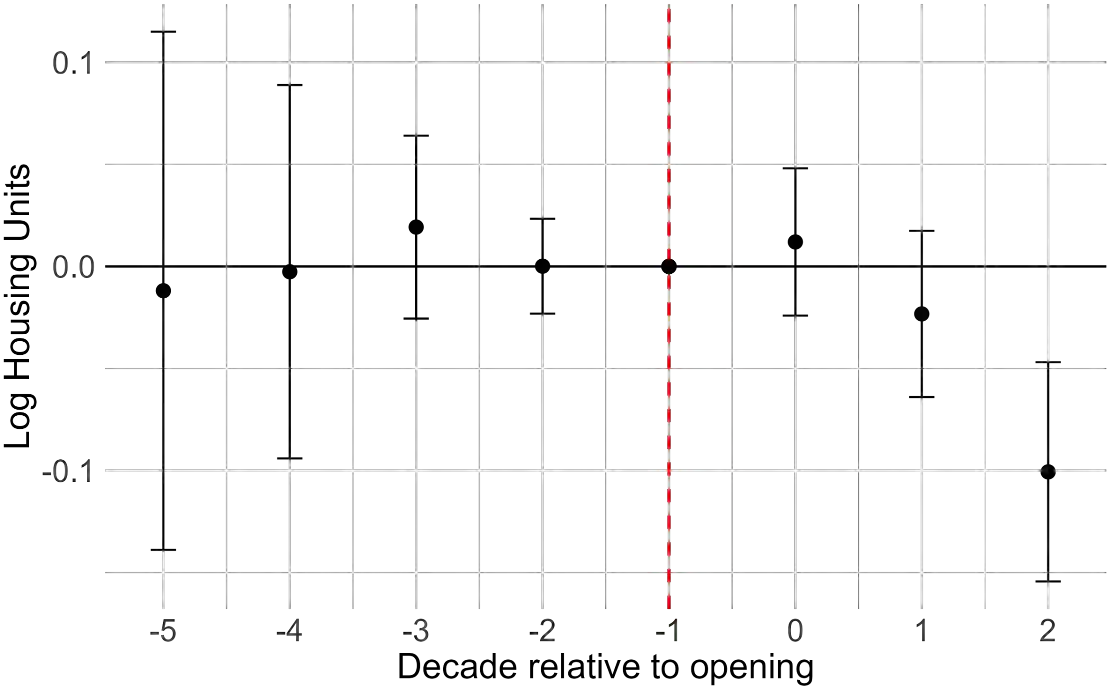


Figure A3: Event Study: Rail Trail Effects on Log Number of Housing Units (Full Sample)

Note: Event study estimates for Greater Boston region, excluding tracts within 2 miles of the city center, which may have a distinct development trajectory. Estimated coefficients are relative to the decade prior to trail opening (baseline). Census tract characteristics are observed every ten years. Standard errors are Conley-adjusted with a two-mile spatial cutoff.

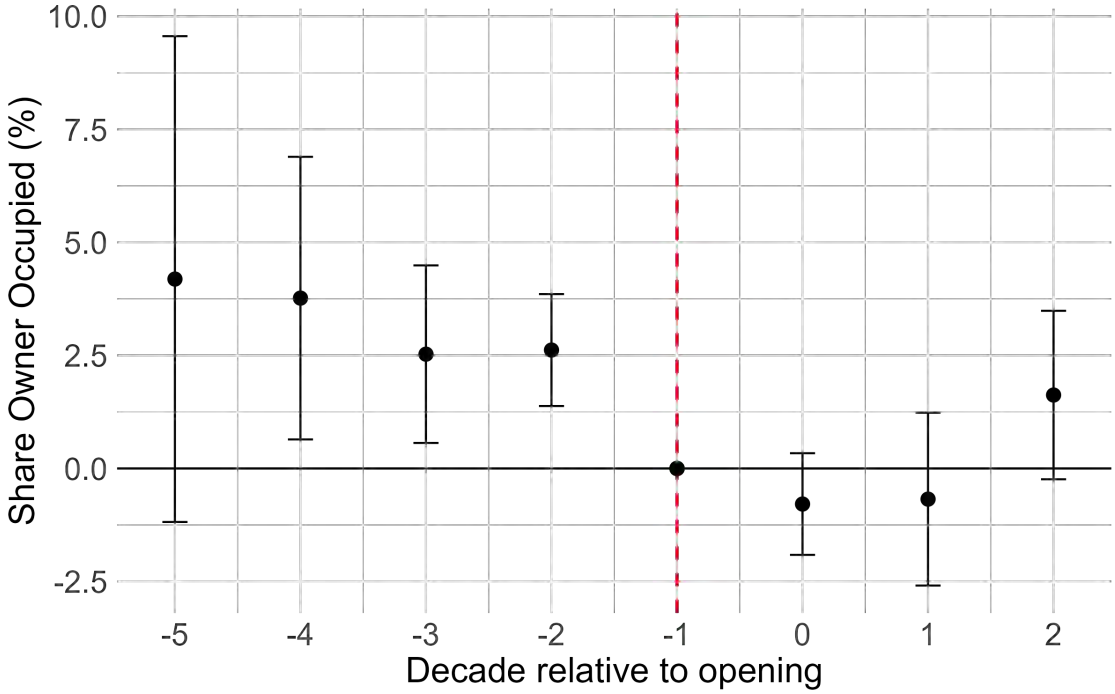


Figure A4: Event Study: Rail Trail Effects on Share of Owner-Occupied Housing (Full Sample)

Note: Event study estimates for Greater Boston region, excluding tracts within 1 mile of the city center, which may have a distinct development trajectory. Estimated coefficients are relative to the decade prior to trail opening (baseline). Census tract characteristics are observed every ten years. Standard errors are Conley-adjusted with a two-mile spatial cutoff.

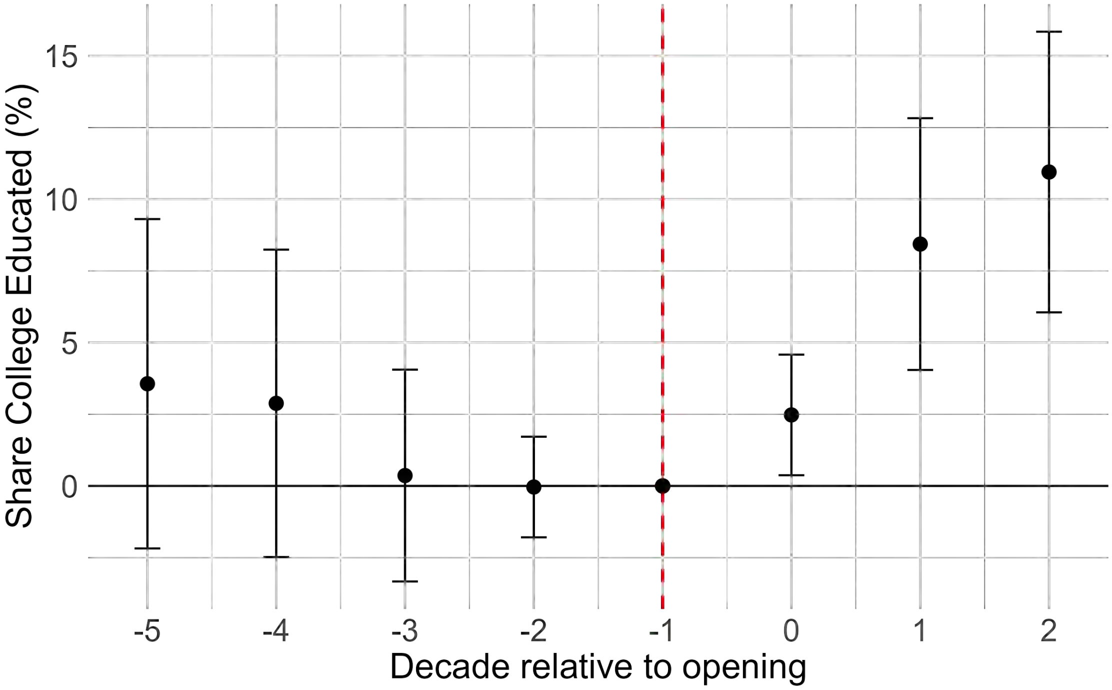


Figure A5: Event Study: Rail Trail Effects on Log Median Household Income (Full Sample)

Note: Event study estimates for Greater Boston region, excluding tracts within 1 mile of the city center, which may have a distinct development trajectory. Estimated coefficients are relative to the decade prior to trail opening (baseline). Census tract characteristics are observed every ten years. Standard errors are Conley-adjusted with a two-mile spatial cutoff.

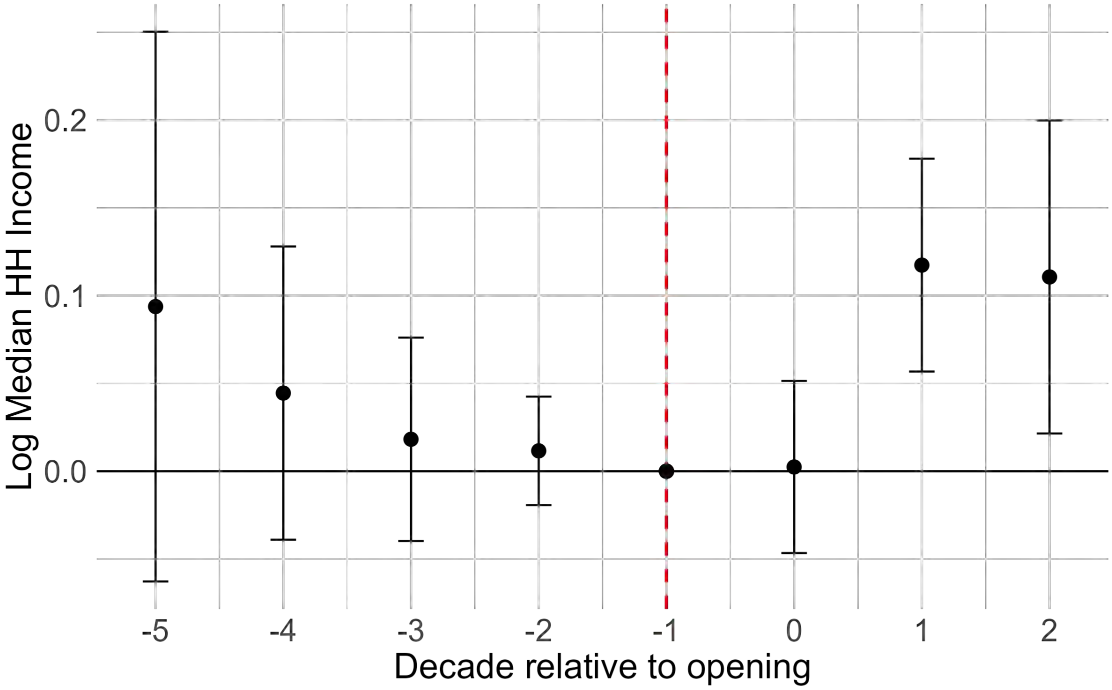


Figure A6: Event Study: Rail Trail Effects on Log Median Household Income (Full Sample)

Note: Event study estimates for Greater Boston region, excluding tracts within 1 mile of the city center, which may have a distinct development trajectory. Estimated coefficients are relative to the decade prior to trail opening (baseline). Census tract characteristics are observed every ten years. Standard errors are Conley-adjusted with a two-mile spatial cutoff.

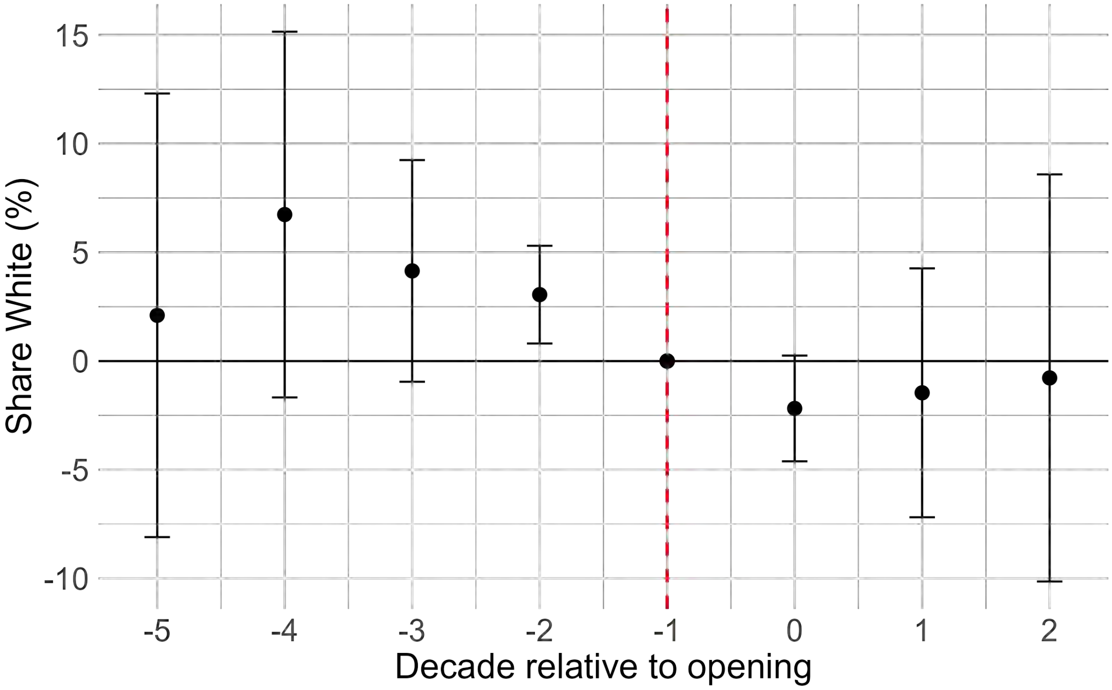


Figure A7: Event Study: Rail Trail Effects on Share of White Population (Full Sample)

Note: Event study estimates for Greater Boston region, excluding tracts within 1 mile of the city center, which may have a distinct development trajectory. Estimated coefficients are relative to the decade prior to trail opening (baseline). Census tract characteristics are observed every ten years. Standard errors are Conley-adjusted with a two-mile spatial cutoff.

A.2 Tables

Table A1: Dynamic Effects of Rail Trail Openings on Housing Outcomes in Greater Boston

	Dependent Variable					
Event Time (k)	Log Median House Value		Log Housing Supply		Share Owner Occupied (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
$k = -5$	0.0752	-0.0175	-0.0119	0.0653	4.1901	0.5210
	(0.0779)	(0.0624)	(0.0647)	(0.0620)	(2.7404)	(2.5241)
$k = -4$	0.1223	-0.0203	-0.0026	0.0356	3.7687^{*}	0.3405
	(0.0828)	(0.0468)	(0.0466)	(0.0551)	(1.5941)	(1.5102)
$k = -3$	0.0135	-0.0304	0.0193	0.0546	2.5284^{*}	0.5975
	(0.0347)	(0.0243)	(0.0228)	(0.0333)	(1.0015)	(1.0890)
$k = -2$	0.0187	0.0141	0.0001	0.0173	2.6196^{***}	1.3687
	(0.0369)	(0.0367)	(0.0118)	(0.0161)	(0.6314)	(0.8650)
$k = 0$	0.0264	0.0646^{**}	0.0120	0.0044	-0.7870	-0.5019
	(0.0261)	(0.0272)	(0.0184)	(0.0215)	(0.5734)	(0.7263)
$k = +1$	0.1404^{*}	0.1705^{***}	-0.0233	-0.0531^{*}	-0.6784	0.9977
	(0.0551)	(0.0496)	(0.0208)	(0.0320)	(0.9749)	(1.3156)
$k = +2$	0.1595^{*}	0.2097^{***}	-0.1007^{***}	-0.1409^{***}	$1.6245^{\cdot}$	3.7082^{**}
	(0.0806)	(0.0673)	(0.0274)	(0.0379)	(0.9504)	(1.5834)
$k = +3$	0.2371^{*}	0.4045^{***}	0.0189	-0.0166	-3.9631^{*}	-0.5249
	(0.1189)	(0.0885)	(0.0376)	(0.0581)	(1.9611)	(2.6119)
Sample	Full	Corridor	Full	Corridor	Full	Corridor
Observations	2,337	578	2,482	580	2,380	580
Adjusted R^2	0.9137	0.9572	0.8405	0.9128	0.9503	0.9681

Note: Event-study estimates using the Sun–Abraham estimator with tract and year fixed effects. The omitted category is the decade prior to opening ($k = -1$). Standard errors are Conley-adjusted with a 2 mile cutoff. Columns labeled "Full" use all tracts outside the urban core as controls. Columns labeled "Corridor" restrict the sample to tracts along existing or planned rail trail corridors. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A2: Dynamic Effects of Rail Trail Openings on Demographic Outcomes in Greater Boston

	Dependent Variable					
Event Time (k)	Share College Educated (%)		Log Median Household Income		Share White (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
$k = -5$	3.5657	4.2821	0.0938	-0.0353	2.1041	2.3091
	(2.9290)	(2.8761)	(0.0799)	(0.0598)	(5.2039)	(5.9030)
$k = -4$	2.8830	4.0761	0.0445	-0.0090	6.7393	4.0448
	(2.7336)	(2.7868)	(0.0426)	(0.0424)	(4.2904)	(5.0048)
$k = -3$	0.3637	1.0198	0.0182	-0.0172	4.1466	2.7421
	(1.8838)	(2.0851)	(0.0295)	(0.0301)	(2.6004)	(3.0378)
$k = -2$	-0.0362	-0.0679	0.0116	-0.0058	3.0554**	1.6653
	(0.8947)	(1.0469)	(0.0158)	(0.0168)	(1.1462)	(1.2488)
$k = 0$	2.4781*	1.7643$^{\cdot}$	0.0024	0.0242	-2.1812$^{\cdot}$	-0.1837
	(1.0726)	(1.0264)	(0.0250)	(0.0243)	(1.2405)	(1.1536)
$k = +1$	8.4375***	7.6889***	0.1174***	0.1316***	-1.4616	2.0683
	(2.2391)	(2.2866)	(0.0309)	(0.0322)	(2.9198)	(2.4703)
$k = +2$	10.9507***	9.6569***	0.1106*	0.1378***	-0.7766	4.6585
	(2.4961)	(2.7179)	(0.0455)	(0.0429)	(4.7754)	(4.1972)
$k = +3$	19.8395***	17.9098***	0.3868***	0.4570***	3.8240	10.3736**
	(3.2722)	(3.5599)	(0.1078)	(0.0955)	(4.7379)	(5.1984)
Sample	Full	Corridor	Full	Corridor	Full	Corridor
Observations	2,384	581	2,379	578	2,386	581
Adjusted R^2	0.9118	0.9000	0.8299	0.9091	0.8533	0.8001

Note: Event-study estimates using the Sun–Abraham estimator with tract and year fixed effects. The omitted category is the decade prior to opening ($k = -1$). Standard errors are Conley-adjusted with a 2 mile cutoff. Columns labeled “Full” use all tracts outside the urban core as controls. Columns labeled “Corridor” restrict the sample to tracts along existing or planned rail trail corridors as designated by the Massachusetts Priority Trails Network. *p<0.1; **p<0.05; ***p<0.01.

Appendix B Event Study Using 1980 Census Mapping

As a robustness check, I replicate the Greater Boston event study in Section 3 using census tract boundaries harmonized to 1980 definitions. While the main analysis uses 1970-harmonized tracts to ensure geographic consistency over the full 1970–2020 period, that choice comes with a tradeoff: many growing areas that were sparsely populated in 1970 are aggregated into large tracts, limiting spatial granularity. Using 1980 as the harmonization base offers finer locational resolution, better capturing urban and suburban development patterns by that time. However, this comes at the cost of losing the 1970 census wave, resulting in a shorter panel from 1980 to 2020. The rest of the event study setup—including treatment timing, outcome definitions, and estimation strategy—remains unchanged.

My sample, restricted to tracts with planned or existing rail trails, consists of 99 census tracts across 5 census waves. I observe similar effects for housing, and more precise estimates of the impacts on race. Results using the 1980-based panel are presented below.

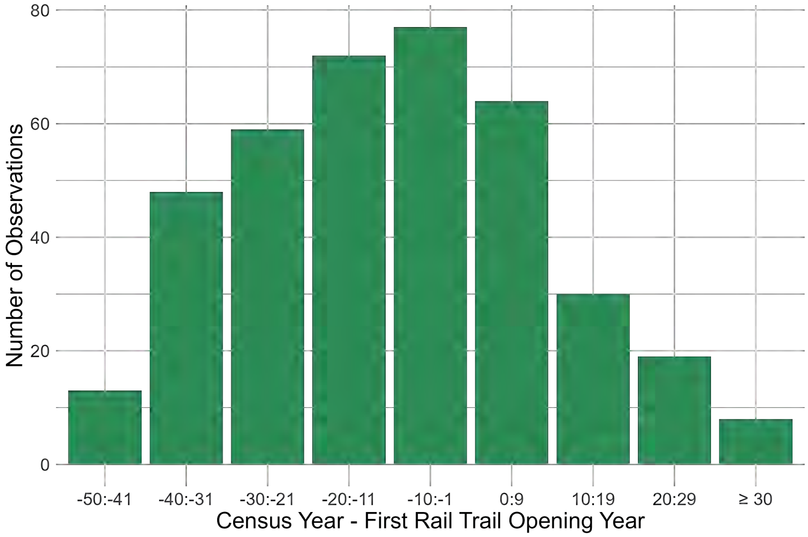


Figure A8: Distribution of Event Times (1980–2020 Panel, 1980-Harmonized Tracts)

Note: This figure shows the distribution of event times from combining rail trail segment opening dates with a panel dataset from 1980 to 2020, harmonized to 1980 boundaries. Event time is defined as the difference between the Census year and the corresponding trail opening year. Since the census is conducted every ten years, I then group my event time into decade bins.

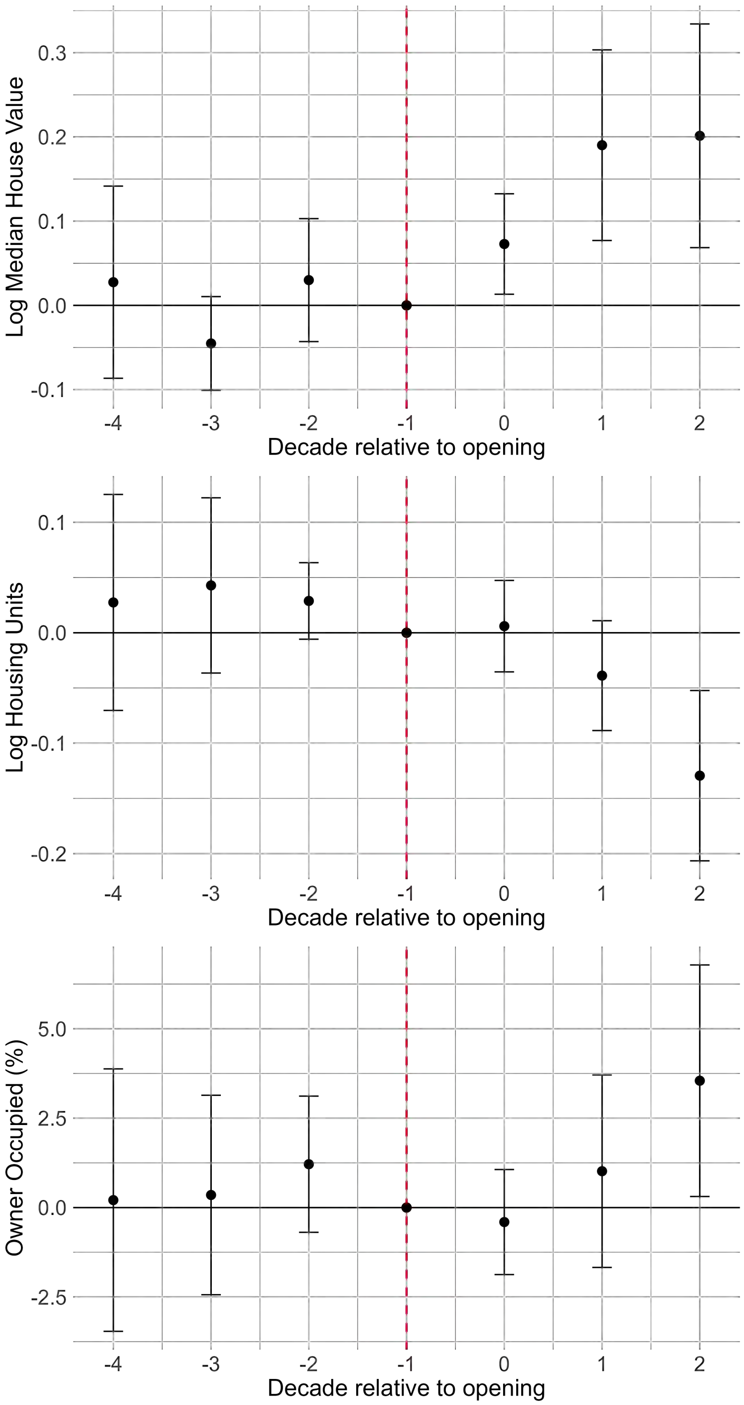


Figure A9: Event Study Results - Housing

Note: This figure shows estimated event study coefficients for the effect of trail openings on log median housing value, and log housing supply, and owner occupied housing share in the Greater Boston area, using a panel dataset from 1980 to 2020. Observations are restricted to tracts that have existing or planned rail trails. The omitted period is the decade prior to trail opening. The omitted category is the decade prior to trail opening. Standard errors are Conley adjusted with a 2 mile spatial cutoff.

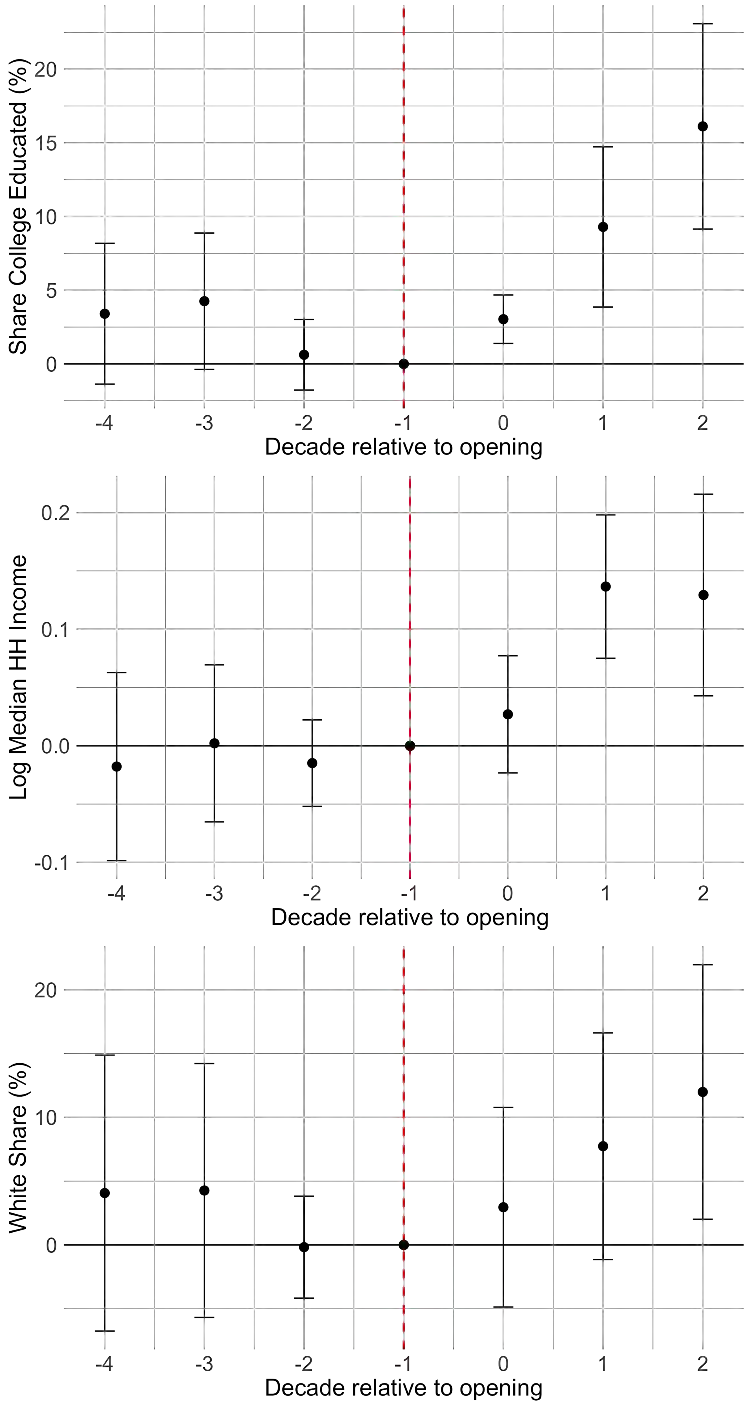


Figure A10: Event Study Results - Demographics

Note: This figure shows estimated event study coefficients for the effect of trail openings on college educated share, and log median household income, and White share in the Greater Boston area, using a panel dataset from 1980 to 2020. Observations are restricted to tracts that have existing or planned rail trails. The omitted period is the decade prior to trail opening. The omitted category is the decade prior to trail opening. Standard errors are Conley adjusted with a 2 mile spatial cutoff.

Appendix C IV Using Actual Abandoned Rail

As an alternative to the connectivity-based algorithm for predicting abandonment, I use the presence of actual abandoned rail lines as an instrument for trail creation. This choice was motivated by the basic logic of the rail-to-trail process: corridors must first be abandoned before they can be converted into trails. Thus, abandonment is a natural predictor of trail siting and provides a straightforward way to generate instrumental variation.

However, abandoned rail is not an ideal instrument. Abandonment may itself influence neighborhood outcomes directly, for example through the loss of industrial activity, disinvestment and blight. These direct channels risk violating the endogeneity principle and could bias IV estimates. Here, I include results with actual abandoned rail as an instrument to provide a benchmark against which the connectivity-based instrument can be compared.

C.1 Empirical Strategy

To generate exogenous variation in trail creation, I use abandoned rail presence as an instrument for multi-use trail presence. As the United States' network of rail trails has been developing over the past 60 years, I employ a long differences approach to address the issue of staggered trail openings. Specifically, I look at the change in outcome between the present and 1960, before there were any rail trails.

The system of equations to be estimated is:

$$\Delta Y_{ij} = \pi_0 + \pi_1 \Delta \widehat{has\_trail}_{ij} + \gamma \mathbf{X} + \epsilon_{ij} \tag{C1}$$

$$\Delta has\_trail_{ij} = \alpha_0 + \alpha_1 has\_abandoned_{ij} + \rho \mathbf{X} + \omega_{ij} \tag{C2}$$

where ΔY_{ij} is the change in the outcome of interest (for example, log median housing value) in 1960 tract i, 2020 tract j, Δhas_trail_{ij} is the change in the presence of multi-use trails, and $\mathbf{X}$ is a vector of location controls, including presence of active rail and distance to urban center, as well as 1960 baseline controls. In alternate specifications, I use county and municipality fixed effects. Standard errors are Conley-adjusted with a 2 mile spatial cutoff. When a 2020 tract overlaps multiple 1960 tracts, each overlap is treated as a separate observation and weighted by the proportion of the 2020 tract's area within the corresponding 1960 tract. Income and house values have been adjusted to 2020 dollars for consistency across time.

I assume that there were no multi-use trails in 1960 and treat the observed presence of trails today as representing the total change in trail creation over this period. While the opening date of the first official rail trail in 1964 is well-documented, my dataset does not include historical information on abandoned rail that were unofficially used as trails prior to this period. Nevertheless, I argue that it is reasonable to assume that most of these trails, regardless of their historical origins, were not functioning as the multi-use trails we recognize today.

The Federal-Aid Highway Act of 1956 allocated substantial funding to create the United States' highway system, explicitly excluding bicycles and offering no equivalent support for bikeways due to limited demand. This lack of investment created a feedback loop favoring motor vehicle use and highway expansion, suppressing the development of non-motorized infrastructure. Bicycle use began to use resurge in the United States in the 1960s, coinciding with the opening of the first rail trail (Reid 2017). Thus, although some trails may have existed in other forms prior to this period, their function as accessible green spaces for non-motorized, multi-use purposes was likely minimal. For these reasons, it is reasonable to treat the current presence of multi-use trails as indicative of the change in trail availability since 1960.

Abandoned rail presence can serve as a valid instrument for trail presence if the following conditions hold: (1) it is positively correlated with trail presence (relevance), (2) it is effectively as-good-as-randomly distributed across census tracts (independence), (3) it cannot cause a reduction in trail presence once assigned (monotonicity), and (4) it affects demographic changes solely through the channel of rail trail creation, without any other direct influence (exclusion restriction).

First-stage estimates in Table A3 show that abandoned rail presence is a strong and statistically significant predictor of trail development, satisfying the relevance condition. Given the small size of the units of analysis (census tracts with a median area of approximately 0.8 square miles), the presence of abandoned rail can be treated as quasi-random at the local level, conditional on fixed effects and observed controls—meeting the independence assumption.

The institutional context, particularly the National Trails System Act Amendments of 1983—which permitted railroads to relinquish responsibility for unprofitable rail lines by transferring them to qualified agencies for interim trail use—provides a strong basis for asserting that monotonicity holds.

Finally, the parallel pre-trends observed in the Greater Boston event study provide empirical support for the exclusion restriction assumption, as they indicating that abandoned rail lines were not systematically associated with pre-existing trends in housing values or income. Additional robustness checks are presented in Section C.3.

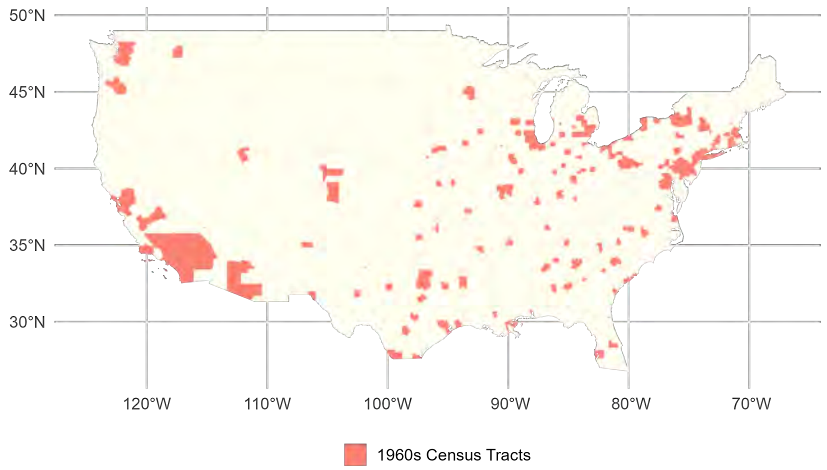


Figure A11: Scope of Census Tracts in 1960

Note: This figure illustrates the areas covered by the 1960 census tract. Due to the smaller U.S. population in earlier decades, this dataset does not cover the entire country, but includes include the largest cities and selected surrounding areas.

C.2 Results and Discussion

Tables A4 and A5 presents the two-stage least squares estimates of the relationship between trail creation and long-run neighborhood change from 1960 to 2020.

Housing Effects. Columns 1–6 of Table A4 show that trail creation is associated with substantial changes in the housing stock. In both county and municipal fixed effects specifications, the presence of a trail leads to a statistically significant increase in median house values—about 16.6% in the county FE model and 8% in the municipal FE model. New housing development also responds: the share of new construction increases by over 4 percentage points, and the share of multi-family housing rises by 3.5–3.8 percentage points, significant across specifications. These findings indicate that trails are viewed as desirable neighborhood amenities, triggering investment in the built environment and potentially supporting densification through multi-unit housing. The effect on owner occupancy is mixed. While the point estimates suggest a decline in owner occupancy—as much as 3.5 percentage points in the municipal model—these estimates are not uniformly significant.

Demographic Effects. Table A5 shows that trail presence also shapes the composition of the residential population. In the county FE model (Column 1), median household income increases by 6.4%, a statistically significant effect. However, this result is near zero and not significant in the municipal FE model (Column 2), suggesting sensitivity to fixed-effects structure. More consistently, trail creation is associated with a large and statistically significant increase in the share of white residents: 11.8 percentage points in the county FE model and 6.7 percentage points in the municipal model.

Taken together, these results suggest that trail creation is associated with substantial long-run neighborhood change, particularly through rising home values, increased housing development, and shifts in racial composition. The results support the view that trails are perceived as desirable amenities, likely driving demand and capitalizing their benefits into property prices. These effects echo broader findings on green infrastructure, which often lead to increased property values and potential fiscal benefits through expanded tax bases.

The income results complicate the broader narrative. In a pure gentrification story, trail development would have attracted in-migration of higher-income households, and one would expect to see clear, sustained increases in neighborhood median income. In the Greater Boston event study, median household income does increase significantly—albeit more slowly than housing values—suggesting that in-migration over time brought in higher-income residents.

However, in the national long-differences analysis, the income effects are relatively modest and sensitive to model specification, particularly when comparing county vs. municipal fixed effects. This contrast invites several interpretations. Instead, the consistent and sizeable increase in the white population share points to demographic sorting along racial or cultural lines. This contrast invites several interpretations.

First, regional variation in housing markets and baseline income inequality likely plays a role. Greater Boston is a high-demand, supply-constrained metro area where small amenity differences (like trail access) can have outsized effects on both property values and the kinds of households willing and able to pay for them. In such markets, trail development likely attracts higher-income households who are already competing for scarce urban housing, leading to parallel increases in both home prices and median income.

In contrast, many areas in the national sample—particularly in the Midwest or South—have looser housing markets and lower overall housing cost baselines. In those settings, trails can still raise property values through improved quality of life, but they may attract moderate-income, white households rather than truly affluent ones. The resulting demographic change is visible in racial composition, but not necessarily in income levels.

Another explanation is differential persistence of incumbent residents. In areas with high homeownership, long-term residents—including lower-income homeowners—may stay even as neighborhoods gentrify physically. This holds down observed income growth, even as property values surge. In Greater Boston, stronger market pressures and higher turnover may make median income more sensitive to neighborhood change.

Table A3: First Stage Predictions of Trail Access

	Dependent variable:					
	Δ Has Trail					
	(1)	(2)	(3)	(4)	(5)	(6)
Has Abandoned	0.182***	0.185***	0.178***	0.177***	0.174***	0.173***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Location FE	County	Muni	County	Muni	County	Muni
Area Weighted	yes	yes	yes	yes	yes	yes
Geography Controls	no	no	yes	yes	yes	yes
1960 Baseline Controls	no	no	no	no	yes	yes
F-stat	529	482	501	435	512	448
Observations	116,199	116,197	116,199	116,197	110,719	110,718
Adjusted R^2	0.193	0.284	0.196	0.287	0.215	0.296

Note: This table presents first-stage estimates of the relationship between abandoned rail presence and multi-use trail presence. "Has Abandoned" indicator for whether a given 1960 tract / 2020 tract combination contains any abandoned rail line. All standard errors are Conley-adjusted with a 2 mile spatial cutoff, and estimates are weighted by the proportion of each 2020 census tract that overlaps with the corresponding 1960 census tract. 40% of obs contain any trail. 23% of obs contain any abandoned rail.

Geography Controls: has active rail, distance from urban center, land area

1960 Baseline Controls (selected via LASSO): median household income, share white, share foreign born, share college educated, commute type, industry, median house value, share multi family housing, share owner occupied housing, share new housing stock

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A4: IV Estimates of Trail Presence on Housing Changes

	Dependent variable:							
	Δ Log Median House Value		Δ Share New Housing (%)		Δ Multi-Family Housing (%)		Δ Share Owner Occupied (%)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Has Trail (Predicted)	0.154***	0.077**	4.401***	4.405***	3.464**	3.843**	-1.596	-3.493^{**}
	(0.042)	(0.039)	(0.859)	(0.937)	(1.601)	(1.764)	(1.506)	(1.620)
Location FE	County	Muni	County	Muni	County	Muni	County	Muni
Area Weighted	yes	yes	yes	yes	yes	yes	yes	yes
Geography & 1960 Baseline Controls	yes	yes	yes	yes	yes	yes	yes	yes
Mean Outcome	$293,994	$293,994	-34%	-34%	15%	15%	-8%	-8%
Observations	105,841	105,840	109,448	109,447	109,477	109,476	109,448	109,447
Adjusted R^2	0.671	0.750	0.884	0.893	0.169	0.213	0.325	0.386

Note: This table presents two-stage least squares estimates of the relationship between trail presence and housing changes. The endogenous variable is the change in "has trail," an indicator for whether a given 1960 / 2020 area combination contains a trail. The instrument is whether the unit has an abandoned rail.

Geography Controls: active rail, distance from urban center, land area

1960 Baseline Controls (selected via LASSO): median household income, share white, share foreign born, share college educated, commute type, industry, median house value, share multi family housing, share owner occupied housing, share new housing stock

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A5: IV Estimates of Trail Presence on Demographic Changes

	Dependent variable:			
	Δ Log Median HH Income		Δ Share White (%)	
	(1)	(2)	(3)	(4)
Has Trail (Predicted)	0.062***	0.016	11.800***	6.654***
	(0.038)	(0.040)	(2.203)	(2.115)
Location FE	County	Muni	County	Muni
Area Weighted	yes	yes	yes	yes
Geography & 1960 Baseline Controls	yes	yes	yes	yes
Mean Outcome	$31,098	$31,098	-35%	-35%
Observations	108,712	108,711	109,770	109,769
Adjusted R^2	0.519	0.598	0.462	0.616

Note: This table presents two-stage least squares estimates of the relationship between trail presence and population demographic changes. The endogenous variable is the change in "has trail," an indicator for whether a given 1960 / 2020 area combination contains a trail. The instrument is whether the unit has an abandoned rail.

Geography Controls: active rail, distance from urban center, land area

1960 Baseline Controls (selected via LASSO): median household income, share white, share foreign born, share college educated, commute type, industry, median house value, share multi family housing, share owner occupied housing, share new housing stock

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

C.3 Robustness Checks

A potential threat to validity arises if abandoned rail corridors directly affect property values or residential composition, or are correlated with unobserved factors that affect those outcomes. For instance, if the presence of abandoned rail lines raises concerns about safety or attracts activities considered undesirable by the surrounding community, their presence could depress housing demand or influence the sociodemographic profile of nearby residents, violating the exclusion restriction assumption of the instrument.

I test whether my IV model predicts changes in housing values, household income, and racial composition from 1950 to 1960. This period is well suited for a placebo test, as it preceded the first decade of the first rail trail creation. I instrument for the change in "has trail" exactly as in the main analysis, but any fitted value during this decade can only come from the spatial pattern of abandoned rail lines, not from actual trail construction. If this model yields significant results estimating changes in housing and demographics in a decade without rail trails, then that would suggest it's picking up other factors besides rail trail creation.

Table A6 reports these placebo IV estimates. Across housing prices, household income, and racial composition, the coefficient on Predicted Trail is small and statistically indistinguishable from zero. In other words, abandoned rail presence did not predict neighborhood change in the pre-treatment decade.

This null result strengthens the interpretation of the 1960–2020 estimates. Because abandoned rail corridors show no detectable relationship with economic or demographic trends before trails existed, the positive post-1960 effects are unlikely to be artifacts of pre-existing growth trajectories.

Table A6: IV Estimates of Trail Presence on Neighborhood Changes, 1950-1960 (Placebo)

	Dependent variable:			
	Δ Log Median House Value (1)	Share New Housing (%) (2)	Δ Log Median HH Income (%) (3)	Δ Share White (%) (4)
Has Trail (Predicted)	−0.027	−2.889	−0.033	1.803
	(0.024)	(2.207)	(0.023)	(2.387)
Location FE	County	County	County	County
1950 Baseline Controls	yes	yes	yes	yes
Mean Outcome	$2,607	23%	$1,477	-5%
Observations	11,099	11,154	11,154	11,157
Adjusted R^2	0.503	0.621	0.327	0.124

Note: This table presents ordinary least squares estimates of the relationship between abandoned rail presence and changes in log median house value, log median household income, and the share of the white population.

Geography Controls: distance from urban center, land area

The 1950 Baseline Controls include population density, the share of the population with a college degree, the share of the population that is foreign-born, and historical measures of the outcome variables of interest from 1960. All standard errors are Conley-adjusted with a 2 mile spatial cutoff, and estimates are weighted by the proportion of each 1960 census tract that overlaps with the corresponding 1950 census tract.

*p<0.1; **p<0.05; ***p<0.01.

Appendix D Exploring Heterogeneity in Housing Supply Change

This section investigates why rail trails reduce housing supply in Greater Boston (Section 3) while increasing it in the national analysis (Section 4). Specifically, I explore whether differences in local housing supply elasticity help explain this divergence.

I map census tracts to the elasticity estimates from Saiz (2010), which are based on geographic constraints on developable land and land use regulations circa 2000. Tracts are partitioned into three groups: inelastic (elasticity < 1), moderately elastic ($1 \leq$ elasticity $<$ 2), and highly elastic (elasticity ≥ 2). I re-estimate the main IV specifications within each group. Because not all 1970 census tracts fall within metropolitan areas covered by Saiz (2010), I also report estimates for the full sample to facilitate comparison. Table A7 confirms that the first stage remains strong across all samples, with historical rail abandonment strongly predicting trail creation and F-statistics well above conventional thresholds.

Table A8 displays the two-stage least squares estimates of trail effects on housing values and supply by elasticity bin. The results are rather surprising, as they seem to be contradictory the event study findings. Housing value effects are positive across all elasticity categories but most precisely estimated in markets with at least moderate supply responsiveness (14–17 percent). In the most inelastic markets, the point estimate is smaller (11 percent) and imprecise. By contrast, the supply response is positive and significant in the inelastic and moderate bins (19-25 percent) but near zero and insignificant in highly elastic markets.

This pattern appears to contrast with the Greater Boston event study, where housing prices increased while supply decreased in treated tracts relative to not-yet-treated tracts. This suggests that there are other reasons explaining why Boston's dynamics differs substantially from other low-elasticity counties in the sample. First, the temporal horizon differs substantially: the IV estimates capture 50-year changes from 1970 to 2020, while the event study focuses on shorter-term dynamics around trail construction. Most Boston trails were built in the 1980s and 1990s. Supply responses may evolve over time—initial displacement effects could give way to longer-run development as neighborhoods adjust. Second, Boston's unique context—extremely high land values, stringent historic preservation, and limited remaining developable parcels—may generate atypical responses even within the low-elasticity category.

Table A7: First Stage by Housing Supply Elasticity

	Dependent variable:			
	Has Trail			
	(1)	(2)	(3)	(4)
$\widehat{A}$	0.177***	0.209***	0.179***	0.191***
	(0.017)	(0.013)	(0.012)	(0.008)
Has Any Rail	0.108***	0.119***	0.119***	0.118***
	(0.013)	(0.010)	(0.010)	(0.006)
Sample by Elasticity	< 1	1-2	> 2	All
Share Abandoned	0.28	0.38	0.42	0.36
Share Trail	0.12	0.16	0.18	0.15
Location FE	County	County	County	County
Geography & 1970 Baseline Controls	yes	yes	yes	yes
F-stat	103	271	233	586
Observations	9,143	10,935	9,917	29,995
Adjusted R^2	0.267	0.250	0.245	0.253

Note: This table presents first-stage regression results using predicted abandoned rail lines as an instrument for actual trail presence. The sample is stratified by MSA-level housing supply elasticity estimates from Saiz (2010). Column 4 includes all observations with available elasticity estimates for comparison with the main specification.

Geography Controls: urban center, distance from urban center, land area.

1970 Baseline Controls (selected via LASSO): log median house value, log median household income, log housing units, housing density, population and population density, housing tenure and structure shares (owner-occupied, single-family, multi-family, by decade built), demographic composition (race, education, foreign-born, employment), commuting mode shares, and industry employment shares.

*p<0.1; **p<0.05; ***p<0.01.

Table A8: IV Estimates of Trail Presence on Housing Changes by Housing Supply Elasticity

	Dependent variable:							
	Δ Log Median House Value				Δ Log Housing Supply			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Has Trail (Predicted)	0.113	0.159^{***}	0.131^{**}	0.172^{***}	0.220^{**}	0.178^{**}	0.045	0.193^{***}
	(0.074)	(0.059)	(0.066)	(0.040)	(0.089)	(0.071)	(0.089)	(0.049)
Sample by Elasticity	< 1	1-2	> 2	All	< 1	1-2	> 2	All
Location FE	County	County	County	County	County	County	County	County
Has Any Rail	yes	yes	yes	yes	yes	yes	yes	yes
Geography & 1960 Baseline Controls	yes	yes	yes	yes	yes	yes	yes	yes
Mean Outcome	$407,037	$127,488	$64,983	$191,805	1,160	1,336	1,788	1,429
Observations	8,975	10,783	9,753	29,511	9,142	10,932	9,916	29,990
Adjusted R^2	0.654	0.663	0.571	0.687	0.515	0.599	0.636	0.574

Note: This table presents two-stage least squares estimates of the relationship between trail presence and housing outcomes. The sample is stratified by MSA-level housing supply elasticity estimates from Saiz (2010). Columns 4 and 8 includes all observations with available elasticity estimates for comparison with the main specification.

Geography Controls: urban center, distance from urban center, land area.

1970 Baseline Controls (selected via LASSO): log median house value, log median household income, log housing units, housing density, population and population density, housing tenure and structure shares (owner-occupied, single-family, multi-family, by decade built), demographic composition (race, education, foreign-born, employment), commuting mode shares, and industry employment shares.

*p<0.1; **p<0.05; ***p<0.01.

Appendix E Why Not Use Distance as a Measure of Access to Trail?

One potential concern with the tract-level coding strategy is that housing market responses may vary by proximity to rail or trail infrastructure. If a trail lies along the border of a census tract, housing in an adjacent tract may also be affected, even though that tract is coded as having no trail in my primary analysis. To investigate this, I construct a tract-level measure of average distance to the nearest rail or trail feature. Specifically, I generate 100 random points within each tract, calculate the distance from each point to the nearest rail or trail segment, and take the average. This measure serves as a proxy for access within each tract and provides a way to capture clustering of rail and trail features along tract boundaries.

Relative to OLS results that use simple presence indicators, the coefficients on trails are somewhat smaller when county fixed effects are included, though they remain positive and of similar magnitude when municipality fixed effects are used. My interpretation is that proximity alone may not fully capture the value of trails as amenities. For trails to function as neighborhood assets, households require convenient access points, and tracts that are geographically close but do not contain a trail may not have easy access. This intuition is consistent with Curtis (2017), who show that nearly half of child pedestrian injuries in one large city occur along census tract boundaries. They argue that this pattern arises because major roads often form tract borders, and these roads both increase accident risks and create barriers for walking and cycling. In the same way, a tract may be "near" a trail in distance terms but separated by infrastructure that makes access costly.

For active rail, the proximity-based coefficients are larger than in the indicator specification. This is unsurprising: active rail generates noise and other externalities that travel beyond tract boundaries. If every point in a tract lies close to active rail, exposure is more pervasive, and thus the negative effects are stronger in the distance specification.

Interestingly, the coefficient on proximity to abandoned rail without a trail is slightly negative and statistically significant. This is somewhat puzzling, since the indicator specification produced null results. Table A11 shows that many tracts that are close to abandoned rail (within 0.5 miles) do not themselves contain any abandoned segments. The negative sign therefore seems to be driven by relatively lower values and incomes in tracts that are adjacent to abandoned rail but do not directly contain it. Why these neighboring tracts are depressed is less clear, but the patterns suggest that adjacency to abandoned infrastructure may have negative associations even if the tract itself does not host the feature.

Table A9: OLS Estimates of Rail and Trail Presence on Housing Characteristics

	Dependent variable:					
	Log Median House Value		Share New Build (%)		Share MultiFamily (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Trail $\leq$ 0.5 mi	0.054^{***}	0.065^{***}	0.150	0.298	5.676^{***}	4.861^{***}
	(0.011)	(0.012)	(0.185)	(0.208)	(0.391)	(0.425)
0.5 $<$ Trail $\leq$ 1 mi	0.012	0.027^{***}	-0.343^{**}	-0.279^{*}	2.028^{***}	1.545^{***}
	(0.009)	(0.009)	(0.155)	(0.169)	(0.313)	(0.347)
Active Rail $\leq$ 0.5 mi	-0.195^{***}	-0.144^{***}	-0.414^{**}	0.177	2.157^{***}	2.012^{***}
	(0.010)	(0.010)	(0.181)	(0.202)	(0.389)	(0.425)
0.5 $<$ Active Rail $\leq$ 1 mi	-0.102^{***}	-0.075^{***}	-0.382^{**}	-0.083	0.476	0.181
	(0.008)	(0.007)	(0.163)	(0.173)	(0.318)	(0.346)
Abandoned No Trail $\leq$ 0.5 mi	-0.065^{***}	-0.027^{**}	0.108	0.476^{**}	3.101^{***}	2.942^{***}
	(0.013)	(0.013)	(0.202)	(0.229)	(0.450)	(0.510)
0.5 $<$ Abandoned No Trail $\leq$ 1 mi	-0.039^{***}	-0.024^{**}	-0.116	-0.022	1.311^{***}	1.136^{***}
	(0.009)	(0.009)	(0.163)	(0.182)	(0.346)	(0.391)
Location FE	County	Muni	County	Muni	County	Muni
1960 Baseline Controls	yes	yes	yes	yes	yes	yes
Mean Outcome	\$426,206	\$426,206	7%	7%	23%	23%
Observations	44,187	44,186	45,594	45,593	45,605	45,604
Adjusted R^2	0.717	0.776	0.184	0.218	0.464	0.465

Geography Controls: distance from urban center, land area

1960 Baseline Controls (selected via LASSO): median household income, share white, share foreign born, share college educated, commute type, industry, median house value, share multi family housing, share owner occupied housing, share new housing stock *p<0.1; **p<0.05; ***p<0.01.

Table A10: OLS Estimates of Rail and Trail Presence on Population

	Dependent variable:					
	Log Median HH Income		Share White (%)		Share Owner-Occupied (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Trail $\leq$ 0.5 mi	0.037^{***}	0.041^{***}	1.784^{***}	3.013^{***}	-3.841^{***}	-2.659^{***}
	(0.010)	(0.011)	(0.654)	(0.706)	(0.403)	(0.426)
0.5 < Trail $\leq$ 1 mi	0.008	0.016^{*}	-0.193	0.987^{*}	-1.921^{***}	-1.029^{***}
	(0.008)	(0.008)	(0.509)	(0.539)	(0.337)	(0.354)
Active Rail $\leq$ 0.5 mi	-0.172^{***}	-0.132^{***}	-5.326^{***}	-3.483^{***}	-7.121^{***}	-5.734^{***}
	(0.009)	(0.010)	(0.560)	(0.552)	(0.393)	(0.422)
0.5 < Active Rail $\leq$ 1 mi	-0.087^{***}	-0.065^{***}	-3.248^{***}	-1.954^{***}	-3.334^{***}	-2.408^{***}
	(0.007)	(0.007)	(0.410)	(0.393)	(0.336)	(0.350)
Abandoned No Trail $\leq$ 0.5 mi	-0.071^{***}	-0.039^{***}	-1.266^{*}	0.264	-5.147^{***}	-3.874^{***}
	(0.012)	(0.013)	(0.697)	(0.724)	(0.433)	(0.490)
0.5 < Abandoned No Trail $\leq$ 1 mi	-0.044^{***}	-0.033^{***}	-0.403	0.185	-2.234^{***}	-1.669^{***}
	(0.008)	(0.008)	(0.508)	(0.523)	(0.354)	(0.392)
Location FE	County	Muni	County	Muni	County	Muni
1960 Baseline Controls	yes	yes	yes	yes	yes	yes
Mean Outcome	\$88,613	\$88,613	58%	58%	60%	60%
Observations	45,352	45,351	45,707	45,706	45,594	45,593
Adjusted R^2	0.467	0.540	0.484	0.606	0.464	0.495

Geography Controls: distance from urban center, land area

1960 Baseline Controls (selected via LASSO): median household income, share white, share foreign born, share college educated, commute type, industry, median house value, share multi family housing, share owner occupied housing, share new housing stock *p<0.1; **p<0.05; ***p<0.01.

Table A11: Census Tract Counts by Proximity to Trail and Rail Infrastructure

Trail Proximity	Has Trail	No Trail	Total
Trail < 0.5 Mile	14,219	4,429	18,648
0.5 $\leq$ Trail < 1 Mile	3,323	8,341	11,664
Trail $\geq$ 1 Mile	1,704	15,615	17,319
Total	19,246	28,385	47,631

Active Rail Proximity	Has Active Rail	No Active Rail	Total
Active < 0.5 Mile	9,210	3,128	12,338
0.5 $\leq$ Active < 1 Mile	3,183	6,519	9,702
Active $\geq$ 1 Mile	1,942	23,649	25,591
Total	14,335	33,296	47,631

Abandoned Rail Proximity (No Trail)	Has Abandoned Rail	No Abandoned Rail	Total
Abandoned < 0.5 Mile	3,928	4,545	8,473
0.5 $\leq$ Abandoned < 1 Mile	1,530	6,341	7,871
Abandoned $\geq$ 1 Mile	1,200	30,087	31,287
Total	6,658	40,973	47,631

I next rerun the IV, which takes the following form:

$$\text{Second Stage:} \quad Y_i = \beta_0 + \beta_1\, \text{trail\_halfmile}_i + \beta_2\, \text{trail\_1mile}_i + \mathbf{X}_i'\gamma + \varepsilon_i$$

$$\begin{aligned} \text{First Stage 1:} \quad \text{trail\_halfmile}_i = \pi_{10} + \pi_{11}\, & \text{abandoned\_halfmile}_i + \\ & \pi_{12}\, \text{abandoned\_1mile}_i + \mathbf{X}_i'\delta_1 + v_{1i} \end{aligned}$$

$$\begin{aligned} \text{First Stage 2:} \quad \text{trail\_1mile}_i = \pi_{20} + \pi_{21}\, & \text{abandoned\_halfmile}_i + \\ & \pi_{22}\, \text{abandoned\_1mile}_i + \mathbf{X}_i'\delta_2 + v_{2i} \end{aligned}$$

When I re-estimate the IV using distance-based measures of predicted abandonment, the results differ considerably from the baseline indicator models. For housing values and incomes, coefficients become negative and highly imprecise, while demographic outcomes fluctuate in sign depending on proximity bands, again with large standard errors. Average distance to rail features is a relevant instrument (first stages are strong), and monotonicity is plausible, but the exclusion restriction is more questionable. A tract where all points are close to rail or trail features is often small and densely connected to many other neighborhood attributes, making it more likely that the instrument also captures unrelated determinants of housing outcomes.

Table A12: IV Estimates of Trail Presence on Housing Changes

	Dependent variable:					
	Δ Log Median House Value		Δ Share New Housing (%)		Δ Multi-Family Housing (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Trail $\leq$ 0.5 mi (Predicted)	-0.057	0.054	2.151	4.411^{**}	11.541^{***}	13.924^{***}
	(0.099)	(0.096)	(1.834)	(1.886)	(3.895)	(4.077)
0.5 $<$ Trail $\leq$ 1 mi (Predicted)	-0.192	-0.180	-1.234	-2.521	11.233^{**}	8.380
	(0.117)	(0.121)	(2.145)	(2.498)	(4.849)	(5.612)
Active Rail $\leq$ 0.5 mi	-0.087^{***}	-0.068^{***}	-0.023	0.264	1.087^{***}	1.353^{***}
	(0.009)	(0.008)	(0.157)	(0.164)	(0.332)	(0.336)
0.5 $<$ Active Rail $\leq$ 1 mi	-0.090^{***}	-0.069^{***}	-0.324^{*}	-0.066	0.192	0.159
	(0.008)	(0.007)	(0.171)	(0.171)	(0.375)	(0.355)
Location FE	County	Muni	County	Muni	County	Muni
Area Weighted	yes	yes	yes	yes	yes	yes
Geography & 1960 Baseline Controls	yes	yes	yes	yes	yes	yes
Mean Outcome	\$293,994	\$293,994	-34%	-34%	15%	15%
Observations	105,841	105,840	109,448	109,447	109,477	109,476
Adjusted R^2	0.640	0.735	0.882	0.890	0.087	0.135

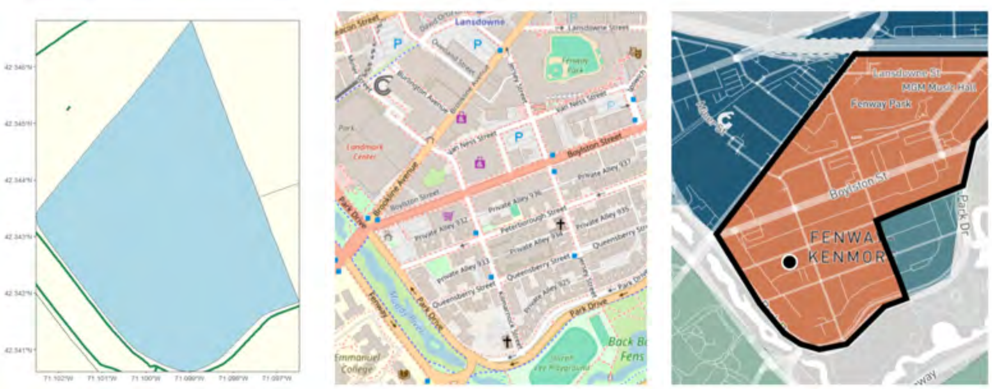
Geography Controls: distance from urban center, land area
1960 Baseline Controls (selected via LASSO): median household income, share white, share foreign born, share college educated, commute type, industry, median house value, share multi family housing, share owner occupied housing, share new housing stock *p<0.1; **p<0.05; ***p<0.01.

Table A13: IV Estimates of Trail Presence on Resident Characteristics

	Dependent variable:					
	Δ Log Median HH Income		Δ Share White (%)		Δ Share Owner Occupied (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Trail $\leq$ 0.5 mi (Predicted)	-0.092	-0.016	-6.248	-1.036	-16.593^{***}	-15.856^{***}
	(0.112)	(0.112)	(5.358)	(5.537)	(4.292)	(4.327)
0.5 $<$ Trail $\leq$ 1 mi (Predicted)	-0.248	-0.230^{*}	6.425	8.404	-13.838^{**}	-10.273^{*}
	(0.123)	(0.123)	(6.457)	(7.017)	(5.426)	(5.982)
Active Rail $\leq$ 0.5 mi	-0.074^{***}	-0.061^{***}	-1.873^{***}	-1.474^{***}	-2.953^{***}	-2.731^{***}
	(0.008)	(0.008)	(0.425)	(0.398)	(0.356)	(0.345)
0.5 $<$ Active Rail $\leq$ 1 mi	-0.075^{***}	-0.060^{***}	-3.178^{***}	-1.891^{***}	-2.656^{***}	-2.179^{***}
	(0.007)	(0.007)	(0.448)	(0.392)	(0.440)	(0.383)
Location FE	County	Muni	County	Muni	County	Muni
Area Weighted	yes	yes	yes	yes	yes	yes
Geography & 1960 Baseline Controls	yes	yes	yes	yes	yes	yes
Mean Outcome	\$31,098	\$31,098	-35%	-35%	-8%	-8%
Observations	108,712	108,711	109,770	109,769	109,448	109,447
Adjusted R^2	0.442	0.559	0.455	0.606	0.159	0.282

Geography Controls: distance from urban center, land area
1960 Baseline Controls (selected via LASSO): median household income, share white, share foreign born, share college educated, commute type, industry, median house value, share multi family housing, share owner occupied housing, share new housing stock *p<0.1; **p<0.05; ***p<0.01.

In trying to reconcile the differences between these tables, and the first two tables, I explore characteristics of the tracts that don't have rail and trail features, but are close to them. Figure A12 shows two examples of census tracts that are adjacent to rail or trail infrastructure but do not contain any themselves. Each panel includes (1) the tract shape and rail/trail features from my dataset, (2) a corresponding OpenStreetMap view of the area, and (3) the same tract in the Opportunity Atlas. These examples suggest that adjacent tracts may be separated by infrastructure like major roads, and such tracts often have lower economic mobility relative to their neighbors that contain the amenity. The presence of physical barriers like large roads makes me suspect that average distance within tract is not necessarily a better proxy for access.



(a) Tract within 0.5 Mile of Trail

(b) Tract within 0.5 mile of Abandoned Rail and Trail

Figure A12: Tracts Near Rail/Trail Features, but don't contain them