Powering Down and Moving On?
Energy Transition, Gentrification, and Local Impacts

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Abstract

As the United States navigates a significant energy transition, marked by the retirement of fossil-fuel power plants and a shift towards renewables, it is crucial to comprehend its impact on local communities. This study leverages comprehensive datasets, including USPS Change of Address data and power plant retirement details, to conduct a nationwide assessment of how the retirement of fossil fuel power plants influences local migration trends and community dynamics during an unprecedented energy transition. Contrary to the typical narrative of gentrification, my findings reveal that the complete retirement of fossil-fuel generators in a region leads to a "stagnation effect," characterized by decreases in both in-migration and out-migration. Despite improvements in environmental quality, plant closure is associated with long-term declines in employment and wages and a modest decrease in housing values. My analysis further reveals that lower-income groups and regions with a higher proportion of Black residents experience an intensified stagnation effect, raising environmental justice concerns. These findings underscore the complex interplay between the advantages and challenges associated with phasing out fossil fuel infrastructure, emphasizing the need for policies to support at-risk communities during the energy transition.

JEL Classifications: Q40, Q53, Q56, R23, J61

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1 Introduction

Over the past decade, fossil-fuel power plants have seen significant retirements in the United States, largely due to a shift towards renewable energy sources, rising regulatory pressure to minimize greenhouse gas emissions, and changes in electricity demand. According to the U.S. Energy Information Administration, coal will account for 85% of U.S. electric generating capacity retirements in 2022. This trend will likely continue due to the ongoing competition from renewable resources, which has sparked interest in how these structural changes in electricity generation may affect local communities. On one hand, power plants provide jobs, tax revenues, and a stable source of electricity (Chatzimouratidis and Pilavachi, 2008; Hondo and Moriizumi, 2017; Mauritzen, 2020). On the other hand, fossil-fueled power plants are associated with disamenities like noise pollution, traffic from fuel deliveries, harmful emissions like sulfur dioxide (SO_2), nitrogen oxides (NO_x), and particulate matter (PM) that can negatively impact human health and the environment, which may have larger effects on low-income and minority communities and other environmental justice (EJ) concerned populations (Depro, Timmins, and O'Neil, 2015; Currie et al., 2015; EPA, 2022).

As the energy transition accelerates, understanding its ramifications becomes increasingly important for policymakers and stakeholders seeking to navigate the complex challenges it poses. I investigate how power plant retirements influence population migration patterns in the United States, particularly in relation to potential socio-economic implications and changes in local amenities. These dynamics are essential for designing policies that support sustainable energy transitions while minimizing potential adverse impacts. As power plants close, the resulting changes in air quality, public health, employment opportunities, and local economies can have far-reaching implications for communities, influencing residential sorting patterns, and potentially exacerbating social and economic inequalities (Currie et al., 2015; Burney, 2020; Komisarow and Pakhtigian, 2021). By examining the interplay between socio-economic consequences and environmental amenity changes, this study aims to provide a comprehensive understanding of the effects of power plant retirements on migration patterns, enabling policymakers to develop targeted interventions that balance competing priorities and facilitate a just transition for affected communities.

In this paper, I present the first national-scale analysis evaluating how migration patterns respond to the retirement of fossil-fuel power generators. My analysis utilizes a novel, granular dataset based on United States Postal Service (USPS) Change of Address (COA) records from July 2018 to December 2022. Unlike previous studies that primarily rely on the Census tract or Internal Revenue Services (IRS) data, which are updated annually at the county level, the USPS COA data offers a higher frequency and more up-to-date view of migration patterns and sorting behaviors at the zip code level on a monthly basis. Specifically, it offers aggregated COA volume originating from and destined to each ZIP code, allowing for a separate examination of in- and out-migration flows. By matching this data to Energy Information Administration (EIA) monthly statistics on power plant retirements, I construct a dataset aggregated to the quarter-zip code level to analyze how fossil fuel phase-outs within a region affect migration over time. To capture the effects of the energy transition, I define the treated group as any zip code that experiences the complete retirement of all fossil-fuel generators within its boundaries.

My analysis reveals three main findings regarding how full fossil fuel plant retirement affects local migration patterns. First, using a staggered difference-in-difference design, I find that the full retirement of fossil-fuel generators significantly impacts local migration patterns, resulting in a net increase in population after the retirement. While previous research has noted a net increase following environmental improvements (Banzhaf and Walsh, 2008), my study further shows that this net increase is driven by a decrease in both inflows and a more substantial reduction in outflows following full retirement. This pattern diverges with traditional narratives of gentrification, where wealthier demographics displace financially disadvantaged or minority groups (Depro et al., 2015). Here, the pronounced concurrent reduction in both inflows and outflows represents a "stagnation effect," capturing residents' dormant migration responses to these major energy transitions. Despite similar net inflow outcomes, the underlying patterns deviate from typical gentrification dynamics.

Specifically, I estimate that the retirement of fossil-fueled generators leads to a reduction of about 30 move-ins and 33 move-outs per zip code each quarter. This reduction represents about 7% to 16% of the average total number of people who typically move in or out of each zip code every quarter. It also translates to a slight yet significant quarterly decrease of 0.3% to 0.7% in both population inflows and outflows for each zip code. In essence, the retirement of fossil-fueled generators is associated with a modest but significant reduction in local migration activity. Long-run estimates using yearly, county-level data from the 2013-2020 IRS data also confirm the overall stagnation effects post-retirement. In order to address potential endogeneity issues of non-random selection of zip codes with fossil-fueled generators and the decision to retire fossil-fueled generators, I conduct additional robustness checks using Coarsened Exact Matching (CEM) and instrumental variable (IV) strategies, which confirm this broader trend of diminished migration following plant closures. Multiple data sources and empirical specifications underscore how plant retirement disrupts local migration flows, leading to stagnation in both population inflows and outflows.

Second, the study delves deeper into the heterogeneity of these stagnation effects across various zip code demographics, including age, income, and racial/ethnic composition. The findings consistently reveal heightened migration stagnation in communities with a higher Black population share, younger residents, and lower-income groups following fossil fuel retirements. Specifically, low-income communities experience a larger stagnation impact on move-outs compared to high-income areas. This also generates a passive net inflow since the decrease in outflows exceeds the decline in inflows. Younger communities exhibit greater migration stagnation following fossil fuel retirements relative to older communities, primarily driven by larger reductions in move-outs. The larger decline in outflows also produces a passive net inflow. Communities with higher black population shares undergo larger stagnation effects on both move-ins and move-outs versus lower share communities.

Third, I explore the potential mechanisms driving the stagnation effects and the heterogeneity. The analysis provides evidence of two key mechanisms shaping the migration impacts of fossil fuel retirements: the decline in economic opportunities post-retirement and the seemingly counterintuitive response to environmental improvements. Utilizing county-by-quarter data from the Quarterly Census on Employment and Wages (QCEW), the results show long-run declines in labor outcomes such as employment, wages, and total contributions (which include both employer and employee contributions to benefit programs). This aligns with the reduced in-migration, suggesting diminishing economic prospects are a salient driver. I also found that retirement leads to an increase in air quality, indicating improved environmental quality. However, contrary to expectations, the retirement of fossil-fuel generators leads to around a 3% decrease in housing value, suggesting that the anticipated amenity improvements post-retirement either don't instantly resonate with residents or are overshadowed by economic considerations.

These adverse housing impacts are more pronounced in high-income and predominantly Black communities, reflecting their disproportionate migration responses. Both groups exhibit housing value declines, but higher-income communities see more out-migration, potentially due to economic losses from high-paying energy job cuts. In contrast, Black communities experience a more pronounced stagnation of both population in- and out-flows. The results reveal an intricate interplay of economic and social dynamics influencing migration after fossil fuel retirement. Plant closures appear to dampen economic opportunities, while amenity improvements go unappreciated or are overshadowed, stagnating mobility, especially among marginalized groups.

This research contributes to the expanding collection of literature regarding the impacts of power plant retirements and energy transitions on local areas. While prior work on the energy transition has focused on the effects of climate change and directed innovation (Acemoglu, Aghion, Barrage, and Hémous, 2023), local labor markets (Hanson, 2023), household financial dynamics (Blonz, Tran, and Troland, 2023), and effects on health and education (Komisarow and Pakhtigian, 2021, 2022), this research uniquely focuses on migration responses and the underlying mechanisms. By illuminating the intricate dynamic of amenity improvements and socio-economic shifts, it offers valuable insights to inform transition policies that support at-risk communities (Carley and Konisky, 2020).

Furthermore, this is among the first national-scale studies to examine how cumulative exposure to environmental enhancements from fossil fuel plant closure shapes residential sorting over time. Given fossil fuel plants accounted for the vast majority of retirements in the past decade, their phase-out serves as a useful proxy for enhancing local air quality. While prior studies have examined one-time amenity shocks like Toxics Release Inventory (TRI) facility emissions (Banzhaf and Walsh, 2008), hazardous waste cleanup under the Superfund program (Gamper-Rabindran and Timmins, 2011), air pollution (Close and Phaneuf, 2017; Kim, 2019; Heblich, Trew, and Zylberberg, 2021), and the announcement of an airport renewal program (Lindgren, 2021), they do not capture the prolonged and accumulating benefits as fossil fuel plants wind down operations and ultimately retire.

This study is among the first to leverage plant closure as a continually intensifying indicator of environmental enhancements. The staggered difference-in-differences design enables a dynamic assessment missing from earlier cross-sectional analyses. By tracing how fossil fuel retirements incrementally shape migration as exposure to environmental gains accumulates, this innovative approach provides insight into how evolving amenity conditions influence residential mobility decisions. This national-scale longitudinal analysis advances our understanding of how communities respond to major shifts in local environmental quality.

This study also connects to the literature examining shifts in migration patterns and community structures following major economic disruptions. Existing work analyzes mobility responses to various shocks and long-term economic declines in distressed regions (Molloy, Smith, and Wozniak, 2011, 2014, 2017; Ramani and Bloom, 2021; Bilal and Rossi-Hansberg, 2021). This research considers the complete retirement of fossil fuel generators as a significant economic shock given its impacts on local labor markets and tax bases. By exploring the interrelationship between migration responses to job losses versus enhanced environmental amenities, this study provides novel evidence of competing effects that shape residential choices. The findings reveal a complicated interplay in which economic considerations may override or reduce responses to amenity improvements after retirement. This analysis illuminates how migration responds to simultaneous and sometimes conflicting forces. The results offer important insights into how residents weigh competing factors when faced with co-occurring economic and environmental shifts. This has broad implications for models of location choice and residential mobility under multidimensional changes.

More broadly, these findings highlight the multifaceted ramifications of the energy transition, which carry important policy implications. As countries continue phasing out fossil fuel plants, understanding the intricate balance between positive and negative impacts becomes crucial. While retirements can lead to improvements in air quality and public health, they may also result in job losses, economic disruptions, and shifts in the housing market that could have long-lasting effects on communities. This research underscores the need for comprehensive transition policies that balance environmental benefits with socio-economic challenges. By providing a thorough analysis of the impacts of plant retirement on migration, this study offers valuable insights into how to support affected residents and prioritize competing needs.

The remainder of the paper is organized as follows: Section 2 provides some background on power plants and their local impacts; Section 3 describes the data sources and presents descriptive statistics; Section 4 discusses the empirical strategy; Section 5 presents the results and robustness checks; Section 6 explores the mechanisms; and Section 7 includes the discussion and conclusion.

2 Background

The retirement of power plants has become an increasingly important topic in environmental policy, as power plants are major sources of greenhouse gas emissions, air pollution, and public health impacts. Power plant retirements can also have significant economic, social, and environmental impacts on the local community, including changes in employment, tax revenue, and property values. These impacts may, in turn, affect migration patterns and sorting behaviors as people respond to changes in the local economic and social environment.

2.1 The Local Impact of Power Plants

Power plant operations can have both positive and negative impacts on the living standards of local residents and communities. On one hand, the construction and operation of a new power plant can yield considerable local economic benefits. Specifically, developing a new power plant can generate new jobs and businesses, spurring increased spending within the local community. Power plants can employ a substantial number of people throughout their life cycle, offering both temporary and permanent jobs that may draw new residents (Hondo and Moriizumi, 2017). Moreover, power plants can serve as a foundation for new businesses and nearby commercial developments, attracting additional enterprises to the area. Chatzimouratidis and Pilavachi (2008) demonstrate that the average job creation for a 500MW power plant in the United States is around 2,500 for most fuel types, including coal, oil, natural gas, nuclear, and hydro-powered plants. Mauritzen (2020) estimates a 2% permanent increase in wages following an investment in a 400MW wind farm.

In addition, power plant operations can boost local tax revenue or state-shared revenue, supporting local public goods like schools and public transportation. De Faria et al. (2017) found that Brazilian counties with newly-built hydropower plants experienced higher GDP and tax revenues during the initial years of development. Taking these factors into account, Christiadi et al. (2021) estimate the overall economic impact of coal and coal-fired power generation on West Virginia's economy in 2019. Their findings reveal that coal mining and coal-fired power generation contributed 13.9 billion dollars in output, 33,300 jobs, 2.8 billion dollars in employee compensation, and 611.3 million dollars in state and local tax revenue. Wei, Patadia, and Kammen (2010) estimate that a combination of renewable energy, energy efficiency, and low-carbon approaches such as nuclear power and carbon capture and storage can generate over 4 million job-years by 2030.

On the other hand, the construction and operation of power plants may result in significant environmental impacts on local communities. Fossil-fueled power plants release a variety of pollutants, including sulfur dioxide (SO_2), nitrogen oxides (NO_x), carbon dioxide (CO_2), mercury (H_g), and particulate matter (PM). These emissions can negatively affect air quality and contribute to respiratory issues (EPA, 2022; Currie et al., 2015). Mercury exposure can increase the likelihood of health problems, such as cancer or immune system damage, for local residents (Driscoll et al., 2013). Moreover, power plant operations can affect water quality due to thermal pollution, chemical spills, or wastewater discharges (Eldardiry and Habib, 2018). These factors can endanger aquatic life and render water unsuitable for human consumption. Power plant construction or operation might also disturb wetlands through land modifications or changes in hydrology. Wetlands offer essential ecosystem services like flood control and wildlife habitats. The construction or operation of power plants can lead to land disturbances or soil erosion, potentially impacting soil productivity and raising the risk of erosion and sedimentation in nearby water bodies (Nickerson, Dobberteen, and Jarman, 1989; Tong and Chen, 2002). Power plant operations produce solid waste, such as ash or sludge, which must be appropriately managed to avoid environmental contamination (EIA, 2022b). Finally, increased traffic related to power plant construction or operation can pose safety hazards for local communities, including heightened truck traffic on local roads or altered traffic patterns near the power plant.

Not all types of power generation have identical environmental impacts. Renewable energy sources like wind and solar power typically exhibit lower environmental effects compared to traditional fossil fuel-based power plants, as they do not release air pollutants or greenhouse gases during operation (Abashidze and Taylor, 2023).

2.2 Retirement Decision of Power Plants

The global energy landscape is undergoing rapid transformation due to factors such as climate change, technological advancements, and shifting policies (Creutzig et al., 2018; Kober et al., 2020). These factors have significantly increased fossil fuel power plant retirements, particularly for those dependent on fossil fuels like coal, petroleum, and natural gas. In the United States, a substantial amount of coal-fired capacity has retired over the past decade, with a record 14.9 GW retired in 2015. Annual coal retirements averaged 11.0 GW per year from 2015 to 2020, decreased to 5.6 GW in 2021, and then increased to 11.5 GW in 2022 (EIA, 2023). Davis, Holladay, and Sims (2022) provide a comprehensive analysis of the history of U.S. coal-fired plant retirements over the last decade and demonstrate the impact of environmental and market forces on coal-fired power plant retirements. They show that $20 per MWh electricity subsidy extends the average life of a generator by six years, while a $51 per ton carbon tax brings forward retirement dates by about two years.

Concern about climate change is a primary driver of power plant retirements (IPCC, 2018). Fossil fuel combustion in power plants is a significant contributor to global carbon dioxide emissions. For instance, in 2021, fossil fuel burning for energy accounted for 73% of total U.S. greenhouse gas emissions and 92% of total U.S. anthropogenic CO_2 emissions (EIA, 2022a). These emissions have been linked to rising global temperatures and severe environmental consequences such as more frequent and intense extreme weather events, melting ice caps, and rising sea levels (Pachauri et al., 2014; Abas, Kalair, and Khan, 2015). As a result, there has been a global push towards cleaner energy sources like wind, solar, and hydropower, which emit fewer greenhouse gases and have a smaller environmental footprint (IRENA, 2020).

Technological advancements in renewable energy generation have made these energy sources increasingly cost-competitive with traditional fossil fuels (Lazard, 2021). Declining costs of solar panels, wind turbines, energy storage solutions, and improved efficiency of energy conversion, have accelerated renewable energy adoption and reduced the economic viability of older, less efficient fossil fuel-based power plants (Newell, Raimi, Villanueva, Prest, et al., 2020; BNEF, 2020). Consequently, many power plant operators are opting to retire these facilities and invest in cleaner, more cost-effective energy sources (EIA, 2023).

Governments worldwide are implementing policies to facilitate the transition to cleaner energy sources and reduce dependence on fossil fuels (IEA, 2020, 2022). These policies encompass carbon pricing mechanisms, renewable energy targets, and subsidies for clean energy projects (Bank, 2022; REN21, 2022). Additionally, stricter environmental regulations, such as limits on air pollutant emissions and water usage, have increased the operational costs of fossil fuel-based power plants, further contributing to their retirement (Maupin et al., 2014; EPA, 2023). Cullen and Mansur (2017) demonstrate how carbon prices drive fuel switching in power plants from more carbon-intensive fuels like coal to cleaner alternatives such as natural gas. Their findings highlight the effectiveness of carbon pricing as a tool for reducing greenhouse gas emissions, emphasizing that such pricing mechanisms can lead to substantial emission reductions even in the absence of renewable energy expansion. This underscores the role of market-based solutions alongside regulatory approaches in guiding the energy transition.

2.3 The Local Impact of Power Plant Retirement

Power plant retirements have a range of impacts on local communities. On one hand, retirements can lead to improved environmental quality as decommissioning power plants reduces local air and water pollution. Burney (2020) finds that between 2005 and 2016 in the continental United States, the retirement of a coal-fired unit was associated with reduced nearby pollution concentrations and subsequent reductions in mortality and increases in crop yield. Komisarow and Pakhtigian (2021) found that areas downwind of closing coal-fired power plants in Chicago experienced a reduction in PM2.5 concentrations between 0.21-0.34 μg/m^3 compared to more distant regions. Improved local air and water quality can increase the appeal of affected areas to potential residents and businesses, potentially raising property values and promoting economic development (Davis, 2011; Muehlenbachs et al., 2015). Improvements in environmental quality and amenities can also make affected areas more attractive to potential residents, influencing migration patterns (Banzhaf and Walsh, 2008; Gamper-Rabindran and Timmins, 2011; Heblich et al., 2021; De Silva et al., 2022).

On the other hand, power plant retirements can result in job losses, revenue loss, and economic disruptions in local communities, particularly in regions heavily reliant on the power generation industry (Carley, Evans, and Konisky, 2018; Houser, Bordoff, and Marsters, 2017; Haggerty et al., 2018). The loss of employment opportunities and income can create a ripple effect in local economies, affecting businesses, public services, and overall community well-being. These employment disruptions may prompt affected individuals to move away in search of new job opportunities or to stay if new employment opportunities arise in other sectors, such as renewable energy projects or industries unrelated to power generation.

Power plant retirements can also have varying effects on property values, through changes in environmental quality, employment opportunities, and public perception. Property values may increase due to improved environmental conditions, or decrease due to job losses and concerns about the local economy (Kiel and Williams, 2007; Davis, 2011). Changes in property values can influence migration patterns, as individuals may be attracted to areas with rising property values or deterred by declining property values (Molloy et al., 2011). The retirement of a power plant may change public perception of the area, potentially influencing migration patterns. For instance, individuals previously deterred from living near a power plant due to pollution concerns or other negative externalities may be more inclined to move to the area once the plant is retired (Chay and Greenstone, 2005; Luechinger, 2009). Conversely, power plant retirement may create a stigma associated with job losses and economic decline, deterring potential residents (Glaeser and Gyourko, 2005).

Government policies and interventions can play a critical role in shaping migration patterns and sorting behaviors following power plant retirements. Policies supporting economic diversification, job creation, and the development of new energy sources can help mitigate the negative impacts of power plant retirements on local communities (Haggerty et al., 2018). Similarly, investments in infrastructure, public services, and community resilience programs can influence migration patterns by enhancing the attractiveness of affected areas to prospective residents (Glaeser and Gottlieb, 2009).

Despite the growing body of literature on the environmental and economic consequences of power plant retirements, a gap remains in understanding how these changes affect local residents' migration patterns and sorting behaviors. This study aims to bridge this gap by examining power plant retirements' impact on migration decisions, offering insights for policymakers navigating the challenges associated with the energy transition. The study offers a comprehensive understanding of the intricate relationships between power plant retirements and individuals' decisions to relocate. This knowledge is important for policymakers and planners in addressing the energy transition challenges, supporting affected communities, and promoting sustainable and equitable development outcomes.

3 Data and treatment indicator construction

This paper leverages a diverse set of datasets encompassing migration patterns, power plant details, employment statistics, and community attributes to investigate the short-term (2018-2022, quarterly) and long-term (2013-2020, annually) effects of power plant retirements on local communities. Table 1 summarizes the data sources used in the study.

3.1 USPS Change of Address Dataset

The primary source for tracking migration patterns is the Change of Address (COA) dataset provided by the United States Postal Service (USPS).[1] The COA service allows individuals and businesses to inform the USPS of new mailing addresses online, by mail, or in-person. The USPS compiles these COA requests on a monthly basis at the ZIP code level, categorizing them by origin and destination as well as move type — family, individual, or business. The dataset provides total COA volume originating from and destined to each ZIP code across move types and includes both permanent and temporary address changes. I focus the analysis on permanent moves, using them as proxies for in-migration (move-in), out-migration (move-out) flows, and net inflows (move-in minus move-out). To protect customer privacy, the USPS only discloses COA volumes greater than 10.[2]

The previous literature primarily relies on Census tract or IRS data to study migration patterns. However, these data are only updated annually at the county level. Additionally, IRS data often underreports information on lower-income households. The USPS COA data is available monthly at the zip code level and thus offers the highest frequency and most up-to-date view of migration patterns and sorting behaviors. Ramani and Bloom (2021) found a strong correlation between the USPS COA and migration patterns in Census datasets, affirming the validity of COA data for capturing migration trends.

3.2 Power Plants Data

I obtain monthly power plant retirement details from the Preliminary Monthly Electric Generator Inventory based on the Energy Information Association (EIA) Form EIA-860M.[3]

[1] Data spanning from July 2018 to July 2022 was obtained via the Freedom of Information Act (FOIA), with recent data available from USPS FOIA Library. The dataset can be downloaded from the website: https://about.usps.com/who/legal/foia/library.htm.

[2] Due to this reporting threshold, the business, family, and individual move counts might not always tally up to the total. In the reported data, these non-disclosed samples appear as blank rather than defined as zeroes. I filled in unreported missing values with the midpoint 5 for permanent address changes, though results remain robust without these values.

[3] See EIA-860M: https://www.eia.gov/electricity/data/eia860m/.

The data details the current status (operating, retired, and planned) of power plant generators, including retirement dates, coordinates, nameplate capacity, and energy sources.[4] Emissions data for CO_2, SO_2 and NO_x from the EIA-923 are matched to generators to incorporate plant environmental characteristics.

To identify the effects of power plant retirement, I construct a treatment indicator centered on the full retirement of all fossil-fuel generators within a region. An illustrative example of this treatment indicator for a specific state is depicted in Appendix Figure A1. My analysis primarily focuses on the full retirement of fossil-fuel generators at the zip code level. I also aggregate monthly data into a quarterly format. This aggregation reduces the noise from monthly fluctuations and smooths out seasonal effects, like summer migrations or holiday staffing patterns, which results in more precise estimates.

3.3 Other Data

In addition, I incorporate data on local community characteristics sourced from the American Community Survey (ACS) 5-year samples, which offer details on median household income, median age, and racial composition.[5] Residential property value changes are gauged using Zillow's Home Value Index (ZHVI) at the ZIP code level.

For a longer-term perspective, I employ the annual Form EIA-860 for power plant retirements and couple it with the IRS migration flow data at the county level.[6] Employment statistics are extracted from the Quarterly Census on Employment and Wages (QCEW) at the county-quarter level, which I then aggregate annually for consistency.

3.4 Descriptive Statistics

Figure 1 shows the monthly number of generator retirements in the U.S. from mid-2018 to late 2022, indicating that fossil fuel retirements, particularly coal, account for the majority during this period. Figure 2 presents the monthly count of ZIP code areas with fully retired generators spanning 2002 to 2022 for all generator types, coal generators and fossil-fueled generators. It reveals a continuous staggered pattern of full retirement of fossil fuel generators across zip codes over time.

[4] To enable merging the EIA data with the zip code migration data, I map the latitude and longitude coordinates to Census tract geometries and their associated zip codes.

[5] The ACS data for 2012 and 2017 derives from the 2008-2012 and 2012-2016 ACS 5-year datasets, respectively.

[6] See EIA-860 (https://www.eia.gov/electricity/data/eia860/) for annual power plant data. For IRS data, I use total inflow and outflow between one county and the rest of the U.S. to match the format of USPS COA data.

Table 2 provides a summary of migration patterns, generator capacity, and emissions at the ZIP code level from 2018Q3 through 2022Q4. Migration patterns are averaged on a quarterly basis, drawn from monthly data sets. The capacity and emissions figures represent average annual metrics from the EPA for individual generators, aggregated up to the zip code level. The sample includes over 30,000 zip code areas. Interestingly, 21% of these zip codes have a power plant. Within these, there's an average of 5 generators per zip code (with a median of 3 and a maximum of 105). A subset of 129 zip codes experienced full retirement of fossil-fueled generators. In the post-retirement phase for these areas, both inflows and outflows of residents dropped, with a concurrent decrease in all emission types—even though capacity witnessed a marginal rise.

I also separate control zip codes into three groups: 1) "Not yet treated" zip areas have experienced retirements of some fossil-fueled generators, but not full retirement. 2) "Never treated" ZIP codes either have no retirements of fossil-fueled units or only possess non-fossil-fueled power plants. 3) "No power plants" zip codes devoid of any power plants during the observed period. The zip codes without power plants consistently demonstrate lower average move-in and move-out rates relative to other groups. However, this group also displays a more significant standard deviation for each mean, pointing to a broader variability across zip code areas. Overall, there's an observed trend of negative net inflow across all samples, accompanied by large, positive standard errors. The net inflow rises for zip codes in the post-treatment phase relative to those in the pre-treatment and not-yet-treated categories.

Table 3 presents summary statistics comparing pre-treatment characteristics of zip codes experiencing fossil fuel retirements to control zip codes, using 2018-2022 ACS 5-year estimates. The data reveals that zip code areas treated with full retirement of fossil-fueled generators exhibit several distinct socioeconomic features. Compared to control areas, the treated zones tend to have a lower median household income, lower median housing unit value, younger median age, and a smaller proportion of white residents. Additionally, they exhibit a higher Gini coefficient, suggesting more income inequality. These areas also house more total and occupied housing units, with a larger proportion of vacant housing units. Furthermore, they tend to have larger average household sizes and total populations. Demographically, the treated ZIP code areas have more substantial representations of Black, American Indian, and Asian populations. These findings suggest that areas undergoing full retirement of fossil-fueled generators tend to be younger, more densely populated, and have a higher concentration of communities of color and lower-income residents.

4 Empirical Strategy

Using the construction of the treatment indicator of full retirement, I can leverage the quasi-experimental variation of fossil-fueled generators' retirement across zip codes and time to estimate the causal impact of such retirements on migration patterns, using a generalized difference-in-differences approach. In this approach, the differences in move-in and move-out populations before and after fossil-fueled generators' retirements are compared between areas with power plants and those without.

The baseline specification for this analysis is a two-way-fixed effect (TWFE) model:

$$Y_{it} = \alpha + \beta D_{it} + \lambda_i + \theta_t + \delta_{ct} + \epsilon_{it} \tag{1}$$

Y_{it} is a measure of internal migration for zip code i in quarter-by-year t. D_{it} is a binary variable equal to one for the full retirement of fossil-fuel generators for zip code i in quarter t. λ_i controls for zip code fixed effect. θ_t is the year-quarter fixed effect, which controls for common time shocks. δ_{ct} is a county-quarter fixed effect, which controls for time-varying unobservables at the county level, including state or county policies and other dynamics affecting migration. The identification assumption for this analysis is that, conditional on controls, the full retirement of fossil fuel generators is as good as randomly assigned (conditional strict exogeneity). Given the potential endogeneity problem that fossil fuel retirements might not be randomly assigned, I employ Coarsened Exact Matching (CEM) methods and Instrumental Variables (IV) approaches that I describe in the following sections. In addition, I implement the heterogeneity-robust estimators for staggered treatment timing proposed by De Chaisemartin and d'Haultfoeuille (2020); Borusyak, Jaravel, and Spiess (2021) ; and Callaway and Sant'Anna (2021) in the appendix, finding results similar to those estimated using TWFE. In all analyses, I cluster standard errors at the region level to match the level of treatment variation (Abadie et al., 2023).

I also estimate a panel event study (Clarke and Tapia-Schythe, 2021) in equation 2 to capture the dynamic effects of fossil-fueled generators' retirement. This approach allows me to estimate migration patterns over time after retirement, which the previous literature using annual data has not studied. It also allows me to test for parallel trends prior to treatment.

For the panel event study, I estimate the following specification:

$$Y_{it} = \alpha + \sum_{k=-8}^{12} \beta_k D_{it}^{(k)} + \lambda_i + \theta_t + \delta_{ct} + \epsilon_{it} \tag{2}$$

where $D_{it}^{(k)}$ represents a set of event-time dummies for each period k relative to the time of power plant retirement. The sum $\sum_{k=-8}^{12}$ indicates that I will estimate a separate coefficient β_k for each lead and lag, ranging from 8 quarters before treatment to 12 quarters after treatment. The reference period (omitted category) is the period right before the power plant retirement.

4.1 Matching Method

One key challenge in identifying effects in Equation 1 is the non-random selection of zip codes with fossil-fueled generators, as suggested by Table 3. Specific demographic areas have disproportionately experienced fossil-fueled generator retirements. To address this concern, I employ Coarsened Exact Matching (CEM) as proposed by Iacus, King, and Porro (2012), using covariates from the 2017 ACS 5-year data and generators data.

CEM is a nonparametric method designed for data preprocessing. It works by addressing potential confounding factors through the reduction of imbalance between the treated and control groups. In this method, data points are grouped into discrete bins based on certain properties. This coarsening ensures exact matches between members within the same bins. However, the bin selection is crucial; it hinges on the covariate distribution. Due to the significant standard deviation from the mean in our dataset, overly granular binning might hinder sample adequacy.

After assessing different coarsening to optimize sample size and balance, I settled on a binning structure based on pre-treatment zip code demographic and generator characteristics, which could potentially influence the relationship between retirement and migration. Specifically, I considered median housing value, total population, generators' lifespan, and the number of generators at the zip code level. The matching coarsens these variables into bins and exactly matches treated and control units with identical bin combinations.

Table 4 presents the balance achieved for key covariates before and after matching. The post-matching results depict well-balanced groups. For assessing balance, both mean differences p-values and Standardized Mean Differences (SMD) were employed. The SMD evaluates the difference in means between the groups, normalized by the pooled standard deviation. Typically, SMD values below 0.1 or 0.2 signify minimal differences between groups (Cohen, 2013). The majority of our variables register values below or close to 0.2, indicating the matched sample sufficiently balances the treatment and control groups. Conditioning on these factors enables estimating the retirement effect by comparing observably similar treated and controlled zip code areas. CEM thus facilitates drawing more valid causal inferences on how full retirement of fossil-fuel generators impacts local migration flows.

4.2 Instrumental Variables Estimation

To address potential endogeneity concerns related to the decision to retire fossil-fueled generators, I employ an instrumental variables (IV) approach. If retirement status is endogenous in Equation 1 due to selection into retirement, the estimated treatment effects will be biased. Retirement decisions for generators can be influenced by a combination of factors: the physical lifespan of the generators, shifts in the energy market, and governmental regulations, to name a few. So I use the generators' lifespan, state-quarter level natural gas prices, state-year level coal prices, and the percentage of natural gas and coal generators as instruments for the full retirement of fossil-fueled generators. The first stage is specified as:

$$\begin{aligned}
\text{FullRetirement}_{ity} = {} & \alpha_0 + \alpha_1 \text{Lifespan}_i + \alpha_2 \text{CoalPriceProxy}_{s,y-1} \\
& + \alpha_3 \text{GasPriceProxy}_{s,y-1} \\
& + \alpha_4 \text{CoalPriceProxy}_{s,y-1} \times \text{Lifespan}_i \\
& + \alpha_5 \text{GasPriceProxy}_{s,y-1} \times \text{Lifespan}_i \\
& + \lambda_i + \theta_t + \delta_{ct} + \epsilon_{it}
\end{aligned} \tag{3}$$

where $\text{CoalPriceProxy}_{s,y-1}$ and $\text{GasPriceProxy}_{s,y-1}$ scale the state fuel prices by the share of retired coal and gas generators to account for different generator mixes:

$$\text{CoalPriceProxy}_{s,y-1} = \frac{\text{Number of retired coal generators}_{ity}}{\text{Total fossil fuel generators}_{ity}} \times \text{CoalPrice}_{s,y-1} \tag{4}$$

$$\text{GasPriceProxy}_{it,y-1} = \frac{\text{Number of retired gas generators}_{ity}}{\text{Total fossil fuel generators}_{ity}} \times \text{GasPrice}_{it,y-1} \tag{5}$$

Subsequently, the predicted $\text{FullRetirement}_{ity}$ from this first stage is used in Equation 1 via a standard two-stage least squares (2SLS) approach. The identifying assumptions are 1) Lifespan affects retirement decisions but not directly migration. Older generators are more likely to retire, 2) Fuel prices affect the profitability of fossil generators. high prices increase retirement likelihood, 3) Fuel price impacts on retirement depend on the generator shares. Coal price matters more in coal-dominant areas, 4) Fuel prices do not directly influence migration patterns. They only operate through retirements. Testing the strength of the first stage and over-identification restrictions helps validate these assumptions. The 2SLS method, combined with examination of the instruments, offers a rigorous approach to estimating causal effects of retirement.

5 Results

5.1 Baseline Results

Panel (a) in Table 5 presents the main TWFE estimates of fossil-fuel generator retirements on migration flows using the full sample and matched sample. Columns (1)-(3) present full sample results, while columns (4)-(6) offer post-matching findings. The results remain consistent between the full and matched samples, though matching yielding slightly smaller effects. Both the full sample and matched sample estimates indicate that full fossil fuel retirement decreases total permanent move-ins and move-outs, while having a small positive but insignificant effect on net move-ins.

In the Panel (b) of Table 5, it reports IV estimates based on the full sample and matched sample. The matching results indicate that full retirement of fossil-fuel generators reduces quarterly move-ins by 30 addresses and move-outs by 33 addresses per ZIP code. These magnitudes are larger than those observed in the OLS estimation. While net inflows remain insignificant across both samples, the larger decline in outflows produces a small positive point estimate. To place these results in context, the average zip code experienced 243 move-ins and 258 move-outs between quarters in 2018. Drawing on the mean move-in and move-out statistics from Table 2, the observed treatment effects imply a shift of approximately 7% to 16% in both population inflows and outflows for each zip code every quarter. According to HUD-USPS Data on Address Vacancies, the average count of addresses at the zip code level was approximately 10,199. By this measure, the inferred move-in and move-out rates equate to a marginal 0.3% to 0.7% decrease in both inflows and outflows each quarter for every zip code. The estimates represent a moderate but meaningful decrease in local migration churn.

Figure 3 displays the event-study results. The coefficients for the eight quarters (two years) preceding full fossil fuel generator retirement in a zip code area are near zero, indicating no discernible pretrends and validating the research design.[7] These findings reveal the dynamics of treatment effects, exhibiting a decreasing trend over time in the post-treatment period for both move-ins and move-outs. The net inflow trend does not become evident until two years after the treatment.

These patterns indicate that fossil fuel retirements gradually reduce local migration dy-

[7] I use full sample to run the panel event study here given the relatively small sample size post-matching, the parallel trends shown in the figure show the basic assumption holds for the full sample to run panel event study and give a good estimate. Appendix Figure A2 presents the event study estimates using the matching sample. Although there is more variance in the treatment effects, it still shows a robust parallel trend pre-treatment, and a decreasing trend, though the post-treatment trajectories are not as sharply delineated as those observed in the full sample representation.

namism over time. While both flows decline, the larger drop in outflows produces a small population retention effect. This implies some increased settlement in communities experiencing fossil-fueled generator closures, likely due to fewer people moving away. However, the overall interpretation remains that retirements decrease mobility and residential churn, and lead to stagnation in local community.

5.2 Heterogeneity

I explore heterogeneous effects of fossil fuel retirements on migration across zip code demographics including age, income, and racial/ethnic composition using 2012 ACS 5-year estimate on zip code level. This sheds light on which types of communities exhibit the greatest sensitivity to energy transition and identify communities that are most vulnerable to such shifts. I pursue two approaches: segmenting the sample by above/below median values for each factor estimating separate models, and interacting the factors with treatment in an augmented TWFE model.[8] Both approaches reveal similar patterns: Younger and lower-income communities experience greater stagnation, driven by move-out reductions. Higher black population share communities see larger effects on both move-ins and move-outs. Native American communities exhibit declines in move-ins but little change in move-outs. Hispanic composition shows minimal differences in effects.

For the subsampling analysis based on the median, I apply equation 1 to obtain estimates within each subsample. Figure 4 presents the results comparison between age and income groups. It shows that low-income zip communities, defined as below median household income, experience a more sizeable stagnation impact on move-outs compared to high-income areas. This also generates a passive net inflow since the decrease in outflows exceeds the decline in inflows. For younger communities, defined as the zip code median age below median age of all zip codes, exhibit greater migration stagnation following fossil fuel retirements relative to older communities. This effect is driven primarily by larger reductions in move-outs. Younger areas also display greater variance in effects. The larger decline in outflows also produces a passive net inflow.

Figure 4 also indicates that zip codes with higher black population shares, defined as above median, undergo larger stagnation effects on both move-ins and move-outs versus lower share zip codes. By contrast, lower white population share communities experience a larger move-out. In addition, low Hispanic composition zip codes do not differ substantially in effects. For Native American communities, the primary impact is a decline in move-ins.

[8] Given a relatively smaller sample after matching, the segmentation based on median ensures sufficient sample size within each subgroup.

In the second approach, I interact the treatment indicator in the TWFE model with the zip code factors to estimate their distributional effects in a joint model (Table 6 and 7). I create a dummy variable equal to one if the factor is above or equal to the median. The results show a similar trend with the sub-sampling coefficients. Higher black share zips see greater stagnation effects with declines in both move-ins and move-outs. White and Hispanic composition shows little difference in effects. Higher Native American shares experience reduced move-ins but not move-outs.

Older communities exhibit a positive interaction effect in a single column. Although this effect isn't statistically significant in the combined estimation presented in column (4), it still implies opposite effects – larger stagnation for younger areas. Likewise, for high-income communities, the treatment effect is noticeably positive in both migrations in and out patterns. This inversion suggests that economically disadvantaged communities experience more pronounced stagnation.

In summary, both approaches suggest that the qualitative patterns of larger stagnation impact more black, younger, and lower-income zip code areas following fossil fuel retirements.

5.3 Long Run Effects

While prior analysis concentrated on the quarterly effects of fully retiring fossil-fueled generators at the zip code level, it is important to examine the persistence or variation of these effects over the long run, especially prior to the COVID era. As the COA data is confined to recent years, I transitioned to a dataset spanning a more extended time frame. In order to maintain consistency with the inflow and outflow setup, I use IRS migration flow data from 2013 to 2020. This dataset includes information on the inflow and outflow of residents between one county and the rest of the U.S., mirroring the definitions found in the COA dataset. Table A1 shows the demographic and generator data summary at the county level, indicating a balanced pre-treatment set between the treated and control groups. Hence, I directly proceed with the TWFE for long-term estimates.

Following equation (1), I integrate the IRS and EIA-860 annual data at the county-year level and estimate the following equation:

$$Y_{cy} = \alpha + \beta D_{cy} + \lambda_c + \theta_y + \delta_{sy} + \epsilon_{cy} \tag{6}$$

Where Y_{cy} represents the migration flow metric for county c in year y. D_{cy} is a binary variable set to one when a county fully retires its fossil-fueled generators. λ_c, θ_y, and δ_{sy} are the fixed effects for county, year, and state-year, respectively. This framework isolates the dynamics of fossil fuel retirements with county and year-fixed effects plus state-by-year trends.

Figure 5 illustrates the event study results on the effects of generator retirement on migration flows, using the TWFE specification. These findings highlight the emergence of stagnation effects three years after retirement. At the county-year level, both move-ins and move-outs diminish, with a stable net inflow trend consistently observed. This suggests that the initial effects observed at the zip code level in the short term begin to manifest more broadly at the county level over the years. The full retirement of fossil-fueled generators seems to discourage migration into the treated county, and residents within these counties appear more inclined to stay put. Over time, this develops into general stagnation within the entire county.

The estimates are significant without state-year fixed effects but become insignificant with them, likely due to unobserved temporal confounders at the state level (Appendix Table A2). However, Appendix Figure A3 without state-year fixed effects displays a similar stagnation pattern as Figure 5 with state-year fixed effects. While the estimates are sensitive to specifications, the general migration response of declining dynamism after retirements is robust across dynamic effect analyses. This highlights the value of exploring both short and long-run effects at multiple geographic levels and through multiple specifications to comprehensively understand the impacts on communities.

5.4 Robustness Checks and Alternative Specifications

This section presents several robustness tests and alternative model specifications to evaluate the reliability and validity of the main results under different assumptions.

Alternative Treatment Setup One concern for the current treatment indication construction using the full retirement of fossil-fueled generators within a geographic area like zip code or county is that it does not consider the position of power plants and its effective areas. For example, if one power plant sits on the edge of one zip code, then its retirement is supposed to affect surrounding areas including multiple zip codes. To address this concern, I follow Davis (2011) to define generators that have buffers overlapping or intersecting with population-weighted centriods will match with the zip codes as the treated group. This method ensure any generator whose buffer influence the certain zip code will be taken into account when consider the full retirement of fossil-fueled generators.

I create 2-mile buffers around each generator as shown in Appendix Figure A4. Appendix Table A3 shows estimates using this buffer-based treatment definition in TWFE models with the full and matched samples. Results display a similar pattern of increasing stagnation after fossil fuel generators full retirements compared to the main estimates. The larger magnitude of effects is likely due to the expanded definition of treatment area under the buffer approach.

I also tried additional specification using zip code centroid-based buffer areas. I create the zip code buffer area based on the smallest, median, and largest radius from centroids to zip code boundary. Power plant generators located inside the smallest buffer will match with the zip code as treated group as Appendix Figure A5 shows. Appendix Table **??** presents the results of smallest zip code buffer using TWFE with full sample and matched sample. This result also shows a stagnation trend for the local migration patterns with a relatively smaller treatment effects. This result can be viewed as a lower bound of the estimates since it only consider the power plants within the smallest zip code population-weighted centroid buffer.

While zip code shapes can complicate centroid-based buffers, the consistency across specifications is reassuring.[9] The stagnation effects are not sensitive to how retirements are geographically linked to zip codes. In both robustness tests, defining treatment based on overlapping geographic areas again produces declining dynamism, validating the main results. The geographic linkage does not change the qualitative stagnation effects, though it does impact magnitude.

Alternative Migration Measurement As robustness, it is also worth trying to estimate effects on migration rates, taking into account the total number of addresses. However, a challenge arises because USPS doesn't directly give us the total address count for each zip code. To navigate this, I utilize data from the United States Department of Housing and Urban Development (HUD). Specifically, HUD receives data on address counts from USPS every quarter, which they then use to create the HUD Aggregated USPS Administrative Data on Address Vacancies. This dataset provides insights into all types of addresses at the census tract level.[10] To align this data with our zip-quarter Change of Address (COA) data, I make use of The HUD-USPS ZIP Code Crosswalk files. These files help map zip code data

[9]It is important to note ZIP code geography can be irregular, unlike standardized areas like census tracts or counties. In some cases, as shown in Appendix Figure A6, population-weighted centroids fall outside the zip code itself. This might be due to measurement errors or the unique shape of that zip code, which limits the precision of centroid-based buffers.

[10]More details are available at The HUD Aggregated USPS Administrative Data on Address Vacancies in website: https://www.huduser.gov/apps/public/usps/home. It's essential to note that while HUD gets this data at a more granular ZIP+4 level, they aggregate it to at least the census tract level before sharing it with the public. About 1% of ZIP+4 records don't align with census tract-level data, likely because of differences in zip code and census tract boundaries.

to other geographical divisions, such as census tracts.[11]

Using the quarterly total address estimates for ZIP code areas from the HUD data, I calculate move-in rates, move-out rates, and net inflow rates for each ZIP code-quarter. These rates are constructed by taking the counts of permanent move-ins, move-outs, and net moves from the USPS COA data and dividing them by the HUD total address figures. This transforms the migration flows into percentage terms, measuring moves as a percent of the total address base.

I then estimate the same TWFE models used in the main analysis, but with the move-in, move-out, and net inflow rates as the outcome variables instead of the absolute move counts. Appendix Table A4 presents the TWFE results for both the full and matched samples using the rate-based outcomes. The estimates show a significant decrease in move-in rates following retirements. The magnitude of decrease move in is 0.7%, which falls the range using absolute effects over mean total address in the main specification. The magnitude of decreasing move out is between 0.9% to 3% with a larger magnitude but insignificant, which could be due to aggregation errors in constructing the total address denominators from the HUD data. Nonetheless, This result validates our main finding again: as the full retirement of fossil fueled generators occurs, the local communities experience low mobilities and stagnation effects on migration patterns.

Robust Estimator for staggered treatments Recent work by Roth, Sant'Anna, Bilinski, and Poe (2023) summarize potential issues with the TWFE model under heterogeneous treatment effects and staggered adoption. They explain that the OLS estimated from static TWFE is a weighted average of 2x2 difference-in-differences across all pairs of time periods and treatment groups. However, it puts negative weight on some comparisons. For example, an early treated unit in a late period can receive negative weight if used as a control for later treated units. This occurs because the TWFE predictions of the treatment indicator fall outside 0/1 bounds. When a late period has many treated units, the predicted treatment for an early adopter exceeds 1. This makes the difference between actual and predicted treatment negative and leads to negative weighting. Then the TWFE coefficient could hypothetically have the opposite sign.

To counter this potential pitfall and ensure the robustness of the results, I use a set of heterogeneity-robust estimators for staggered treatment timing proposed by De Chaisemartin and d'Haultfoeuille (2020); Borusyak et al. (2021); Callaway and Sant'Anna (2021). Appendix Figures A7 and A8 present event studies for move-ins and move-outs estimated

[11]See https://www.huduser.gov/portal/datasets/usps_crosswalk.html

with these robust approaches alongside the TWFE OLS specification. The results exhibit a consistent decreasing trend, a finding that is mirrored across the different robust estimators we employed. This further validate the stagnation pattern shown in the main results.

6 Potential Mechanisms

The full retirement of fossil fuel generators can influence migration through impacts on economic opportunities, amenities, and other local factors. In this section, I delve into the ways the full retirement of fossil fuel generators could shape migration patterns, leading to stagnation effects in local communities.

Economic Opportunities Power plants, particularly those that are fossil-fueled, are deeply intertwined with their local communities, providing employment, contributing to the tax base, and stimulating the local economy. The retirement of these generators can lead to job losses and reduced income, factors that can influence residents' migration decisions, as supported by numerous studies (Blanchard and Katz, 1992; Clark, 1998). To better understand this process, To better understand this, I analyzed annual aggregated county-quarter data from the Quarterly Census on Employment and Wages (QCEW). Applying a log transformation of labor outcomes as outcome variables in equation 6, I observed an overall decline in employment levels, wages, and contributions after the full retirement (See Figure 6). This trend aligns with the short and long-term decrease in migration into these areas, suggesting that diminishing economic opportunities play a significant role in local residents' sorting behaviors.

Appendix Figure A10 presents the effects on the log level of employment across different industries. When breaking down employment into different industries, the average treatment effects do not show specific effects on certain industries, except for public administration. Interestingly, this result does not show an effect on utilities and mining, which could be due to the direct employment effects being absorbed during the retirement process. However, using the log first difference of employment as the outcome variables, Appendix Figure A11 shows that the employment in wholesale trade is significantly negative. This indicates a distinct long-term decreasing trend in wholesale trade employment following the retirement of fossil fuel generators. This provides supporting evidence for the shock to the local economy caused by the full retirement of fossil fuels.

After the full retirement of fossil fuel generators, the effects on economic opportunities might be a reason for fewer people moving into these areas due to the signal of fewer job opportunities. These findings align with previous studies that have linked economic opportunities to migration decisions.

Amenity changes Environmental amenities, or the lack thereof, can have profound implications for residential choices. An extensive body of literature attests to the salience of environmental amenities in influencing migration (Chay and Greenstone, 2005; Banzhaf and Walsh, 2008; Depro et al., 2015). The opening of a power plant, with its associated environmental effects, has been found to decrease housing prices (Davis, 2011; Currie et al., 2015). Conversely, the logic would suggest that the retirement of such plants should improve environmental conditions, thereby exerting upward pressure on housing prices.

My empirical findings seem to reinforce the former but offer a nuanced view of the latter. Using EPA' Air Quality Index annual data as the outcome variables in equation 6 and merge them to the year-county level data, I find that retirement leads to an increase in good days after two years for both absolute value and first difference of good days. It also shows a decrease in days of NO2 for both absolute value and the first difference of days of NO2. This is consistent with literature showing improved environmental quality after retirement (Burney, 2020; Komisarow and Pakhtigian, 2022; Fraenkel, Zivin, and Krumholz, 2022).

To further investigate how retirement affects amenity changes, I use housing prices as a proxy for people's preferences. I use zip-quarter average housing value estimates from Zillow in equation 1. Table 8 shows the effects of full retirement on log housing value across multiple specifications. All the results consistently show a decrease, suggesting that the retirement of fossil-fueled generators leads to around a 3% decrease in housing value. This downtrend is further supported by event-study outcomes (see Appendix Figure A12, which reveals not just post-retirement declines but also anticipatory effects.

This finding is different from the expected increase in housing values post-retirement. While Davis (2011) and Currie et al. (2015) find that the opening of fossil fuel generators and toxic plants leads to significant declines in housing prices, the latter finds negligible effects from toxic plant closures. In contrast, Fraenkel et al. (2022) discover that county-level housing values begin to increase within 6-10 months after coal plant retirement. However, these effects are confined to houses within 15 miles of the first closing unit and are only significant for complete plant retirements. In Komisarow and Pakhtigian (2021)'s zip code level analysis, they find that housing values in ZIP codes near the three coal-fired power plants may have slightly decreased following the closures. Given that this paper analyzes the full retirement of fossil fuel generators at the zip code level in the nation scale, my results can be interpreted as a larger scale analysis compared to Komisarow and Pakhtigian (2021) and an expansive, longer-term analysis relative to Fraenkel et al. (2022)'s results.

Cumulatively, the consistent trend underscores an intriguing phenomenon: the anticipated amenity improvements post-retirement either don't instantly resonate with residents or are overshadowed by economic considerations, as indicated by the depreciation of housing values post-retirement.

A closer inspection reveals an intricate heterogeneity in these effects. Table 9 shows the heterogeneity analysis of different race, age, and income groups' responses to retirement on housing value. This figure shows that housing value decreases more for households with income above the median and for Black communities. The point estimates in both column (3) and column (4) suggest that the decline in housing prices is larger in zip code areas that are above median household income relative to counties that are below the median. The joint estimation of column (6) also shows a full retirement leads to more significant declines in housing value in high Black population share communities, and increases in higher Hispanic communities, although the point estimate is only marginally significant. It also reports an increase in housing value for zip codes where the median age is above median, which shows the housing price is decreasing for areas where the median age is below median.

The housing value results show that high-income communities, which have significantly larger move-outs and slightly less significant (p-value < 0.10) and smaller move-ins as shown in Table 6 and 7, experience migration changes after the full retirement of fossil fuel generators. As BW Research (2020) shows, energy jobs pay about $25.60 an hour, 34 percent more than the median national hourly wage of $19.14 in 2020. Workers in natural gas and coal have the highest median hourly wages of the energy industries. The median wage for solar workers is $24.48 an hour compared with $30.33 for those employed by the natural gas sector, which amounts to a roughly $12,000 annual wage gap. So, the retirement of fossil-fueled generators and lead to job loss and decreasing income, which could drive high-income communities' move-out and lead to housing value declines. This heterogeneity effect also supports the idea that housing value reductions suggest complex amenity transitions where improvements are overwhelmed by other factors. Economic declines may also dominate, as higher income areas exhibit the most negative impacts, alongside the greatest out-migration.

Other Factors There exists a marked differentiation in migratory behaviors and housing value responses across communities, particularly when segregated by income and racial composition. High-income communities demonstrate a pronounced trend of increased outward migration and a decline in housing values as previous results have shown. This migration behavior suggests that residents in these affluent areas possess the resources and flexibility to relocate when faced with economic downturns. The corresponding housing value decline reflects the reduced demand in the wake of significant move-outs.

On the other hand, communities with a high proportion of Black residents tend to experience a more pronounced decrease in both inward and outward migration (Table 6 and 7). This dual movement reduction intensifies the decline in housing values for these communities (Table 8). These evidences suggest stronger stagnation effects compared to communities with a lower proportion of Black residents. Meanwhile, such effects are not observed in communities with a higher white population share.

Several other mechanisms might be at play here. Although there is not direct evidence, one possible explanation for this trend could be the hidden discrimination that Black workers face when seeking job opportunities outside their zip code, as documented in the literature. A body of studies highlights the persistent and covert racial discrimination in labor markets that can impede mobility (see, for instance, Bertrand and Mullainathan (2004)). This systemic discrimination could potentially discourage individuals from moving out of their communities, thereby contributing to the observed stagnation effects.

Moreover, the larger decrease in outward migration observed in lower-income communities could be attributed to the attraction of inexpensive housing for people with low incomes (Figure 4). This aligns with research that suggests that affordable housing can draw individuals with low incomes, thereby contributing to stagnation effects (Ganong and Shoag, 2017; Notowidigdo, 2020; Bilal and Rossi-Hansberg, 2021).

7 Discussion and Conclusion

This national-scale analysis of migration patterns before and after fossil fuel plant retirement provides several important insights into how energy transitions shape residential mobility. The staggered difference-in-differences approach reveals a notable "stagnation effect," with plant closure leading to declines in both in-migration and out-migration flows. This diverges from classic gentrification patterns, instead suggesting that migration into and out of the region becomes dormant.

Investigating potential mechanisms suggests that adverse economic impacts may override amenity improvements in driving migration decisions. Despite retirement increasing good air quality days and reducing NO2, indicating environmental gains, plant closure corresponds with long-run employment and wage declines. Housing values also decrease by around 3% post-retirement, implying amenity benefits are underappreciated or overshadowed by economic considerations.

Moreover, the analysis illuminates disproportionate effects across demographic groups. Areas with more marginalized populations, including higher Black shares, lower incomes, and younger residents, exhibit heightened migration stagnation. This aligns with literature on post-shock migration trends, where economically disadvantaged communities face greater barriers to mobility.

Together, these findings underscore the complex dynamics between the benefits and challenges inherent to energy transitions. On one hand, retiring fossil fuel plants improves environmental quality, reduces pollution, and offers health benefits that can attract residents who value cleaner living conditions. However, closures may also eliminate higher-paying energy jobs, depressing local economic activity and income opportunities. This highlights competing effects in influencing migration decisions, as residents weigh priorities around employment versus environmental amenities. Some may choose to stay and enjoy air quality improvements, while others may pursue job prospects elsewhere. Consequently, plant retirement may reshape community demographics based on preferences across these factors.

These results lend empirical support to calls for policies that consider both positive and negative impacts on local communities. They demonstrate how energy decarbonization can stagnate migration patterns rather than prompting turnover, with economically disadvantaged groups most affected. This underscores the importance of equitable transition strategies to support residents navigating the complex effects of phasing out fossil fuel infrastructure.

This study makes key contributions by providing the first national-scale dynamic analysis of retirement impacts on migration over time. The granular data offers novel evidence that retirement stagnates local mobility contrary to expectations, while highlighting the complex calculus and competing effects underlying migration choices. These insights have important implications for environmental justice and developing policies to facilitate equitable energy transitions across diverse communities.

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Tables

Table 1: Data Sources Summary

	Spatial Unit	Time Range	Frequency
USPS Change-of-address(COA) Data	zip level	2018-2022	monthly
HUD-USPS Data On Address Vacancies	Census Tract	2018-2022	quarterly
Monthly Electric Generator Inventory (EIA-860M)	zip level	2018-2022	monthly
2018 TIGER/Line Shapefiles	zip level	2018	yearly
IRS Migration Data	county level	2013-2020	yearly
EIA-860/923	county level	2013-2020	yearly
ACS 5-year Data	zip/county level	2012-2021	yearly
Zillow Home Value Index (ZHVI)	zip level	2018-2022	monthly
Quarterly Census of Employment and Wages (QCEW)	county level	2013-2020	quarterly

Notes: This table summarizes the key data sources used in the analysis. There are three main categories: (1) Migration data from USPS (July 2018 - Dec 2022) and IRS (2013-2020) to track move-in and move-out, (2) Power plant data from EIA surveys (2013-2022) to identify retirements, capacity, and emissions, (3) Local community data from ACS (2012, 2017), Zillow (2018-2022), and QCEW (2013-2020) on demographics, housing, and employment to consider local impacts. These datasets are aggregated to quarterly-zip and annual-county frequencies to enable examination of both short and long-run effects of plant retirements across various outcomes.

Table 2: Summary Statistics on Zip Code Level, 2018-2022

	Treated Group		Control Groups		
	Pre-treated	Post-treated	Not Yet Treated	Never Treated	No Power Plants
Move in	466	385	485	328	199
	(447)	(407)	(460)	(401)	(333)
Move out	513	414	537	343	209
	(499)	(444)	(532)	(428)	(364)
Net Inflow	-47	-29	-53	-15	-10
	(111)	(98)	(142)	(117)	(82)
Capacity (MW)	256	286	676	187	-
	(538)	(601)	(1,046)	(487)	
CO_2 Emission (Tons)	339,636	222,254	1,222,421	311,407	-
	(1,617,909)	(1,064,086)	(9,225,729)	(2,063,687)	
SO_2 Emission (Tons)	521	240	1,286	384	-
	(4,297)	(1,790)	(11,464)	(5,084)	
NO_x Emission (Tons)	536	331	1,544	461	-
	(2,249)	(1,405)	(7,055)	(2,152)	
Total zip codes	129	129	764	5,678	24,846
N	1,025	1,375	12,899	101,016	447,228

Notes: The table provides a summary of migration patterns, generator capacity, and emissions at the ZIP code level from the third quarter of 2018 through the fourth quarter of 2022. The migration patterns are averaged on a quarterly basis and are derived from monthly data sets. The capacity and emissions figures represent average annual metrics from the Environmental Protection Agency for individual generators, which are then aggregated up to the ZIP code level. The sample includes over 30,000 ZIP code areas.

Table 3: Pre-treatment Summary Statistics for Zip code areas characteristics

	Treated ZIP code areas	Control ZIP code areas
Median Household Income	56,287.38	57,700.20
	(20,630.24)	(24,292.07)
Gini Coefficient	0.43	0.42
	(0.05)	(0.06)
Total Housing Units	7,880.21	4,780.67
	(6,710.55)	(5,946.45)
Occupied Housing Units	7,085.28	4,192.57
	(6,139.01)	(5,393.78)
Median Housing Unit Value	176,353.56	195,166.50
	(128,932.89)	(174,681.76)
Median Gross Rent	891.25	884.44
	(325.59)	(366.23)
Vacant Housing Units	794.92	588.10
	(750.42)	(910.13)
Average Household Size	2.59	2.57
	(0.45)	(0.44)
Median Age	39.95	42.01
	(6.77)	(7.93)
Total Population	19,129.34	11,316.47
	(16,889.10)	(15,026.89)
White Population Ratio	0.80	0.83
	(0.20)	(0.20)
Black	1,984.38	1,427.28
	(4,040.29)	(4,156.70)
American Indian	145.14	89.39
	(600.81)	(374.98)
Asian	901.93	600.57
	(1,977.78)	(2,197.23)
N	2271	491277

Notes: The table provides a comparison of pre-treatment characteristics of ZIP codes experiencing fossil fuel retirements to control ZIP codes, using 2018-2022 ACS 5-year estimates. Areas with full retirement of fossil-fueled generators have distinct socioeconomic features. They typically have lower income and housing value, younger residents, more housing units, larger households, and higher population. They also have higher income inequality and larger Black, American Indian, and Asian populations.

Table 4: Balance table of key covariates for Pre- and Post-Matching Sample

	Pre-Matching				Post-Matching			
	Mean Control	Mean Treated	p-value	SMD	Mean Control	Mean Treated	p-value	SMD
Median Household Income	57,700.97	55,017.14	0.000	0.121	50,674.32	54,942.73	0.000	0.233
Gini Coefficient	0.42	0.43	0.000	0.177	0.43	0.43	0.154	0.046
Total Housing Units	4,786.99	7,508.21	0.000	0.429	5,350.27	7,114.22	0.000	0.284
Occupied Housing Units	4,198.57	6,754.69	0.000	0.440	4,714.90	6,380.05	0.000	0.294
Median Housing Unit Value	195146.57	166498.68	0.000	0.195	138616.35	161999.77	0.000	0.228
Median Gross Rent	884.50	863.12	0.035	0.064	774.65	851.47	0.000	0.273
Total Population	11,331.94	18,527.82	0.000	0.443	12,504.32	17,358.28	0.000	0.313
Median Age	42.01	40.22	0.000	0.235	40.58	40.36	0.319	0.031
White Population Ratio	0.83	0.80	0.000	0.161	0.80	0.80	0.962	0.001
Capacity (MW)	49.56	275.23	0.000	0.481	381.45	282.82	0.000	0.148
Generator Lifespan	38.48	41.06	0.000	0.130	43.69	42.05	0.001	0.100
Number of Generators	1.00	4.84	0.000	0.927	5.02	4.43	0.000	0.169
Zip code areas	31295	126			284	123		
N	562027	1387			3533	1322		

Notes: The table presents the balance achieved for key covariates before and after matching. The post-matching results depict well-balanced groups. Balance assessment was conducted using both mean differences p-values and Standardized Mean Differences (SMD). SMD values below 0.1 or 0.2 typically signify minimal differences between groups. Most variables register values below or close to 0.2, indicating a sufficient balance between the treatment and control groups after matching.

Table 5: The Effects of Full Retirement of Fossil-fuel Generators on Migration

(a) Baseline Results

	Baseline			Coarsened Exact Matching (CEM)		
	(1) Move In	(2) Move Out	(3) Net Inflow	(4) Move In	(5) Move Out	(6) Net Inflow
Fossil Fuel Full Retirement	-23.3***	-31.6***	8.3**	-17.6***	-20.4**	2.8
	(5.7)	(6.3)	(4.0)	(6.7)	(8.0)	(6.2)
Outcome mean	229.5	241.7	-12.2	229.5	241.7	-12.2
Observations	554,892	554,892	554,892	4,826	4,826	4,826
Year-Quarter FE	✓	✓	✓	✓	✓	✓
Zip FE	✓	✓	✓	✓	✓	✓
County-quarter FE	✓	✓	✓	✓	✓	✓

(b) IV Results

	Baseline			Coarsened Exact Matching (CEM)		
	(1) Move In	(2) Move Out	(3) Net Inflow	(4) Move In	(5) Move Out	(6) Net Inflow
Fossil Fuel Full Retirement	-85.5***	-91.2***	5.7	-30.5***	-33.6***	3.0
	(21.8)	(20.3)	(8.9)	(8.9)	(11.1)	(9.0)
Weak IV F-stat	65.6	65.6	65.6	72.3	72.3	72.3
Outcome mean	229.5	241.7	-12.2	229.5	241.7	-12.2
Observations	554,892	554,892	554,892	4,826	4,826	4,826
Year-Quarter FE	✓	✓	✓	✓	✓	✓
Zip FE	✓	✓	✓	✓	✓	✓
County-quarter FE	✓	✓	✓	✓	✓	✓

Notes: This table presents estimates examining zip code-level migration surrounding fossil fuel retirements using OLS and IV estimation. 95% confidence intervals are displayed. This model includes zip, year-quarter, and county-year fixed effects. Standard errors are clustered at the zip code level.

Table 6: Full Retirement and Move In: Heterogeneity by Zip Characteristics

	(1)	(2)	(3)	(4)
Fossil Fuel Full Retirement	25.1*	-32.2***	-31.4***	15.6
	(13.0)	(7.8)	(9.1)	(13.6)
Retirement $\times$ $1_{\geq \text{median}}$(white)	-0.4			-10.6
	(11.3)			(11.3)
Retirement $\times$ $1_{\geq \text{median}}$(black)	-36.2***			-36.5***
	(9.5)			(9.7)
Retirement $\times$ $1_{\geq \text{median}}$(hispanic)	-14.0			-16.7
	(11.2)			(11.2)
Retirement $\times$ $1_{\geq \text{median}}$(indian native)	-23.7**			-22.4**
	(10.0)			(10.2)
Retirement $\times$ $1_{\geq \text{median}}$(Age)		24.1**		15.5
		(10.5)		(10.2)
Retirement $\times$ $1_{\geq \text{median}}$(Household Income)			17.1	18.0*
			(11.0)	(10.3)
Outcome mean	229.5	229.5	229.5	229.5
Observations	554,892	554,892	554,892	554,892
Year-Quarter FE	✓	✓	✓	✓
Zip FE	✓	✓	✓	✓
County-quarter FE	✓	✓	✓	✓

Notes: This table presents heterogeneity estimates examining zip code-level migration on move in considering race, age, and income. This model includes zip, year-quarter, and county-year fixed effects. Standard errors are clustered at the zip code level.

Table 7: Full Retirement and Move Out: Heterogeneity by Zip Characteristics

	(1)	(2)	(3)	(4)
Fossil Fuel Full Retirement	1.5	-42.3***	-48.1***	-14.8
	(17.9)	(8.5)	(9.8)	(18.1)
Retirement × $1_{\geq \text{median}}$(white)	13.9			2.7
	(13.8)			(13.2)
Retirement × $1_{\geq \text{median}}$(black)	-38.4***			-38.5***
	(11.5)			(11.3)
Retirement × $1_{\geq \text{median}}$(hispanic)	-9.6			-16.5
	(12.6)			(12.5)
Retirement × $1_{\geq \text{median}}$(indian native)	-10.5			-7.4
	(11.5)			(11.2)
Retirement × $1_{\geq \text{median}}$(Age)		28.8**		13.9
		(11.9)		(11.3)
Retirement × $1_{\geq \text{median}}$(Household Income)			34.8***	36.3***
			(11.9)	(11.0)
Outcome mean	241.7	241.7	241.7	241.7
Observations	554,892	554,892	554,892	554,892
Year-Quarter FE	✓	✓	✓	✓
Zip FE	✓	✓	✓	✓
County-quarter FE	✓	✓	✓	✓

Notes: This table presents heterogeneity estimates examining zip code-level migration on move out considering race, age, and income. This model includes zip, year-quarter, and county-year fixed effects. Standard errors are clustered at the zip code level.

Table 8: The Effects of Fossil-fueled Generators on Housing Vluae

	TWFE		TWFE-IV	
	(1) Baseline	(2) CEM	(3) Baseline	(4) CEM
Fossil Fuel Full Retirement	-0.024***	-0.031***	-0.062***	-0.036**
	(0.007)	(0.009)	(0.016)	(0.017)
Weak IV F-stat	-	-	72.4	52.3
Outcome mean	12.2	12.2	12.2	12.2
Observations	429,836	4,332	429,836	4,332
Year-Quarter FE	✓	✓	✓	✓
Zip FE	✓	✓	✓	✓
County-quarter FE	✓	✓	✓	✓

Notes: This table presents the effects of full retirement of fossil-fuel generators on housing value. This model includes zip, year-quarter, and county-year fixed effects. Standard errors are clustered at the zip code level.

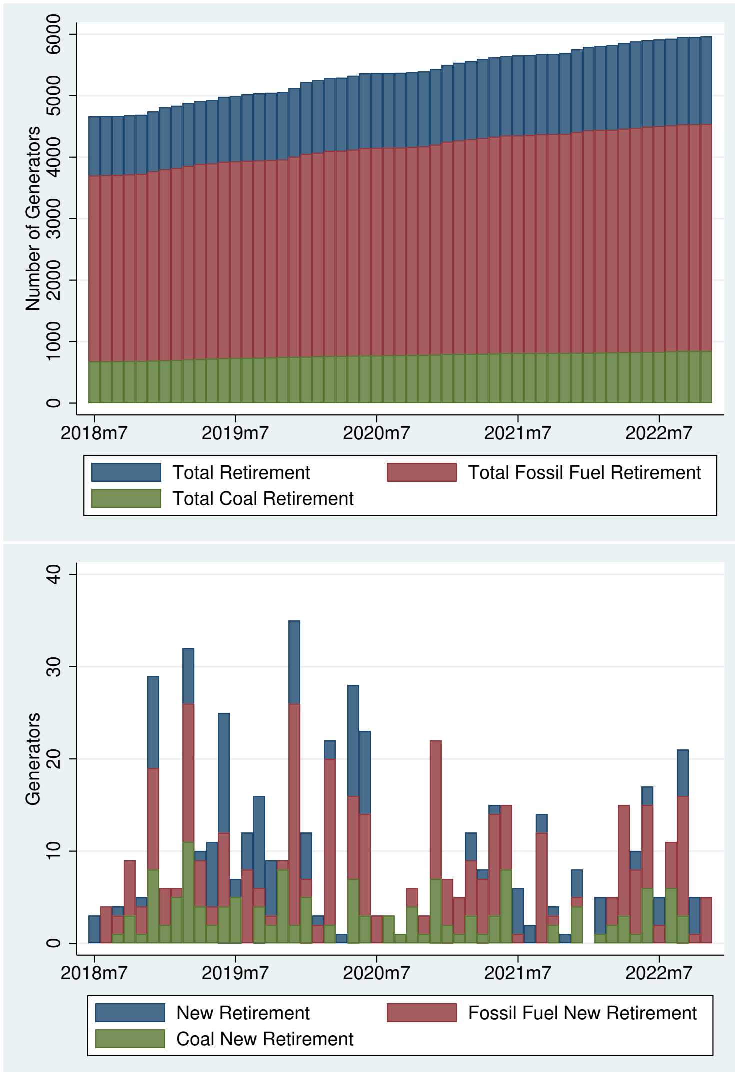
Table 9: The Effects of Fossil-fueled Generators on Housing Vluae

	(1)	(2)	(3)	(4)
Fossil Fuel Full Retirement	-0.011	-0.030***	-0.001	0.004
	(0.023)	(0.008)	(0.011)	(0.024)
Retirement × $1_{\geq \text{median}}$(white)	-0.007			-0.019
	(0.016)			(0.016)
Retirement × $1_{\geq \text{median}}$(black)	-0.028			-0.028*
	(0.018)			(0.017)
Retirement × $1_{\geq \text{median}}$(hispanic)	0.012			0.027*
	(0.016)			(0.015)
Retirement × $1_{\geq \text{median}}$(indian native)	0.003			-0.004
	(0.015)			(0.013)
Retirement × $1_{\geq \text{median}}$(Age)		0.018		0.031**
		(0.015)		(0.013)
Retirement × $1_{\geq \text{median}}$(Household Income)			-0.047***	-0.051***
			(0.013)	(0.012)
Outcome mean	12.2	12.2	12.2	12.2
Observations	429,836	429,836	429,836	429,836
Year-Quarter FE	✓	✓	✓	✓
Zip FE	✓	✓	✓	✓
County-quarter FE	✓	✓	✓	✓

Notes: This table presents heterogeneity estimates examining zip code-level housing value considering race, age, and income. This model includes zip, year-quarter, and county-year fixed effects. Standard errors are clustered at the zip code level.

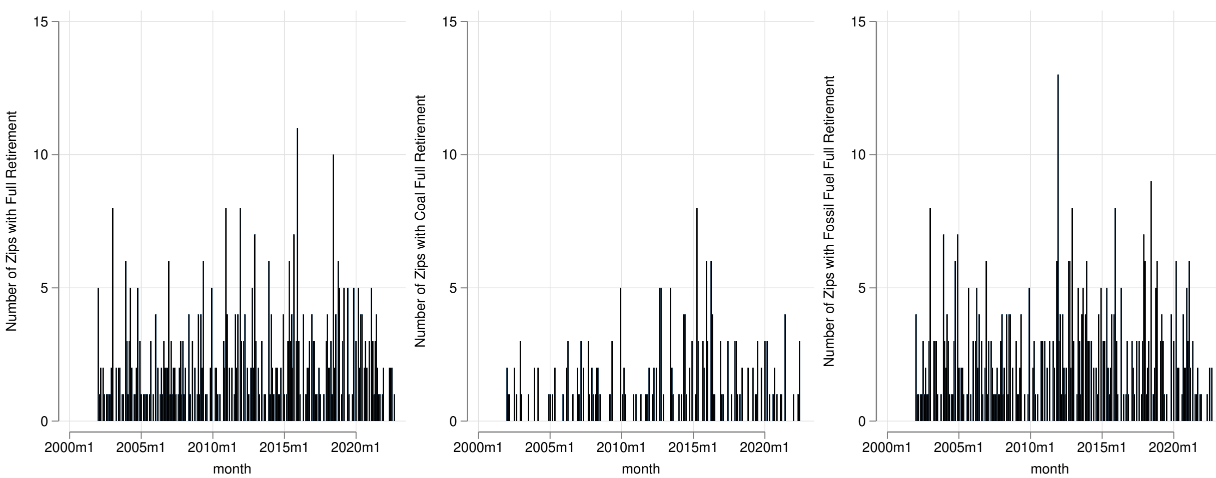
Figures

Figure 1: U.S. generators retirements (2018-2022)



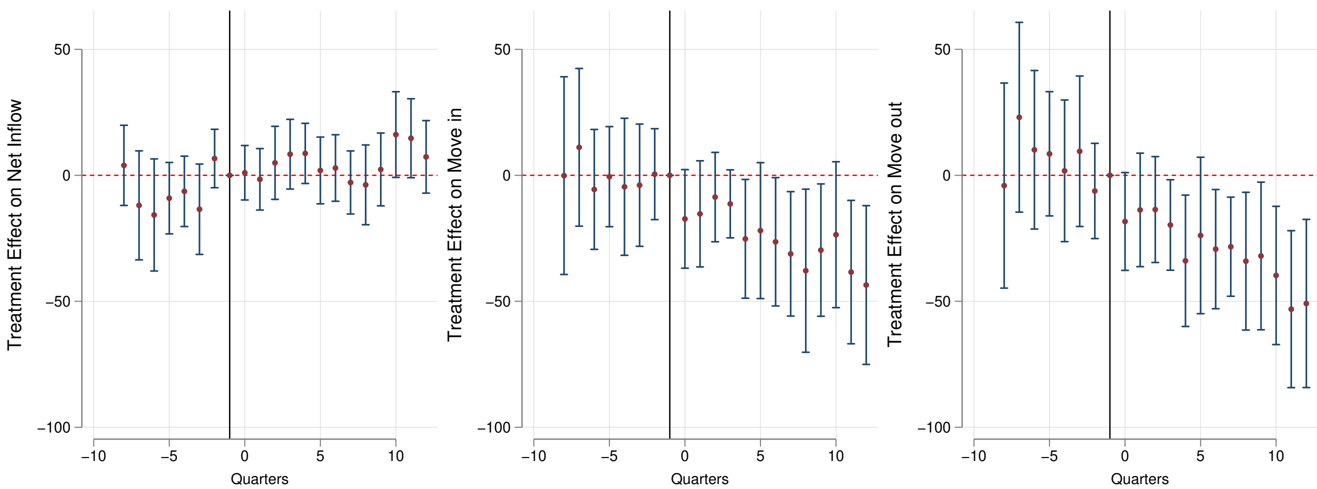
Notes: The figure presents the monthly total retirements and new retirements for all generators, coal-fired generators, and fossil-fuel generators in the United States from July 2018 to July 2022. It highlights that the majority of these retirements are attributed to fossil fuel sources, particularly coal.

Figure 2: U.S. generators retirements on zip code level, 2002-2022



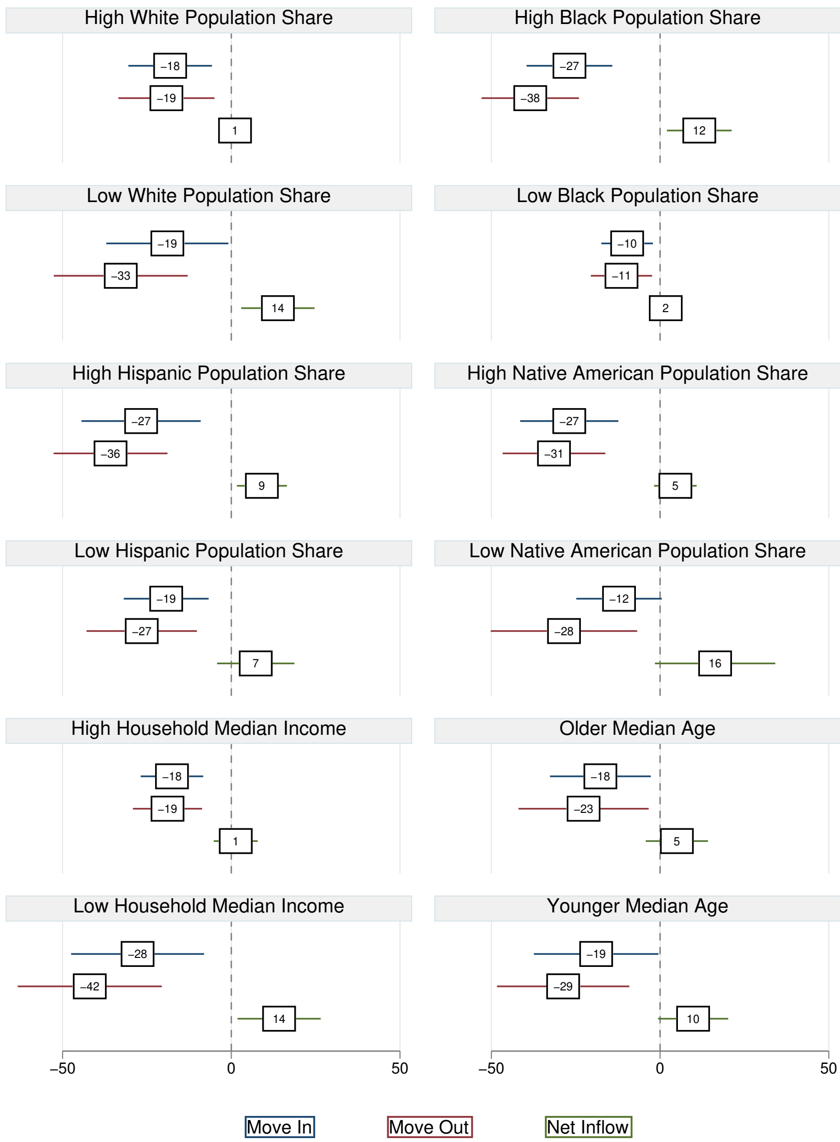
Notes: The Figure displays the monthly count of zip code areas with fully retired generators from 2002 to 2022. This includes all generator types, coal generators, and fossil-fuel generators. The data reveals a consistent, staggered pattern of full retirement of fossil fuel generators across ZIP codes over time.

Figure 3: Impact of Fossil-Fuel Generator Retirement on Migration: Zip-Quarter Analysis



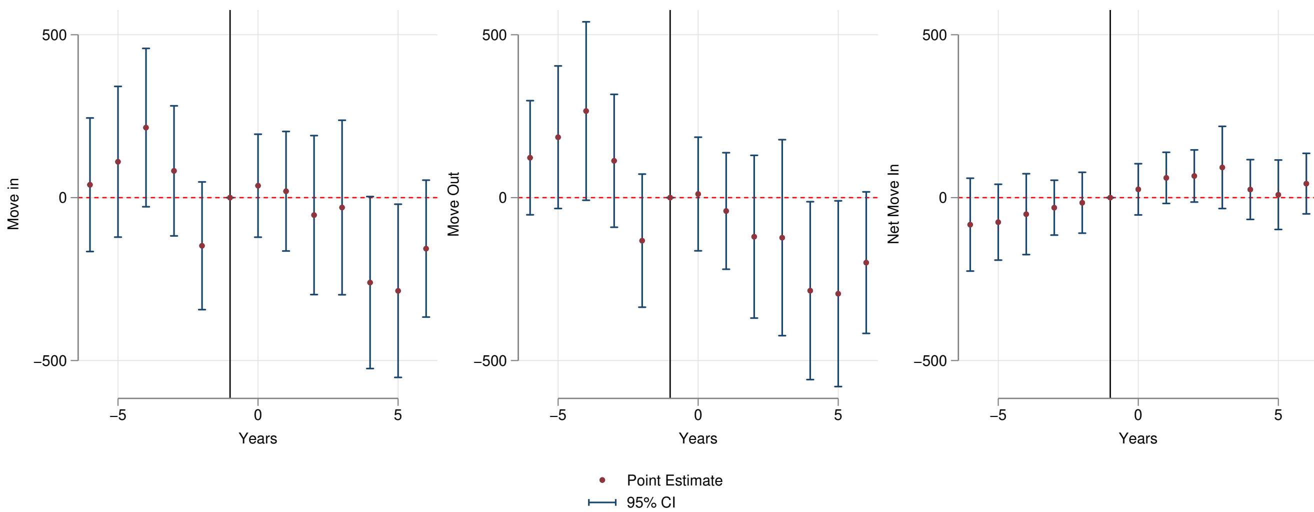
Notes: The figure shows event study estimates from Equation 2 examining zip code level migration surrounding fossil fuel retirements quarterly. Retirement year (0) is omitted as the reference. 90% confidence intervals are displayed. This model includes zip code, quarter, and county-year fixed effects. Standard errors are clustered at the zip code level. The sample covers 2018-2022 IRS migration flows and EIA generator retirements.

Figure 4: Impact of Fossil-Fuel Generator Retirement on Race Groups



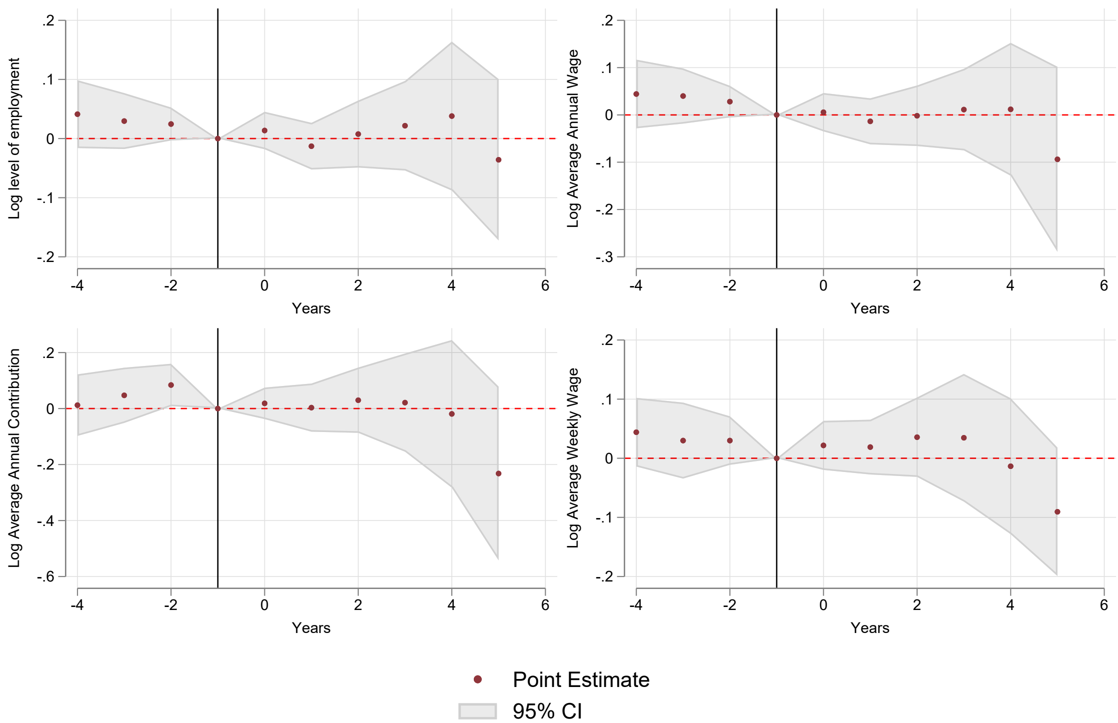
Notes: The figure shows the impact of fossil fuel retirements on migration flows across demographic groups.

Figure 5: Impact of Fossil-Fuel Generator Retirement on Migration : County-Year Analysis



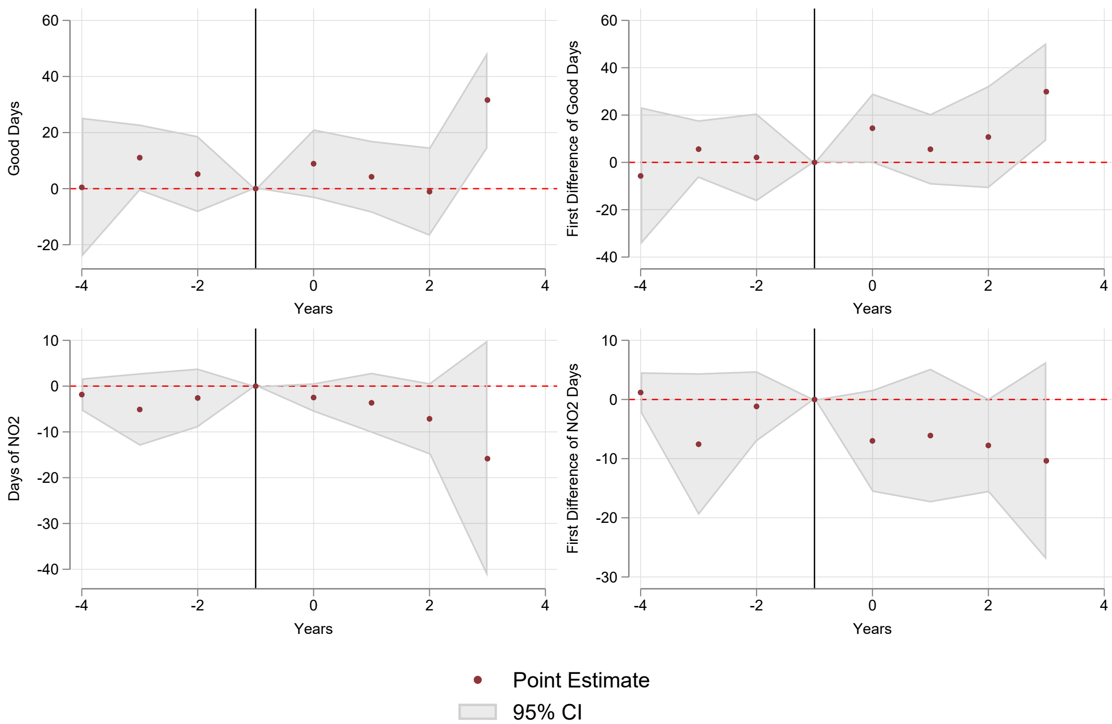
Notes: The figure shows panel event study estimates examining zip code-level migration surrounding fossil fuel retirements using the entire sample. Retirement year (0) is omitted as the reference. 95% confidence intervals are displayed. This model includes zip, year-quarter, and county-year fixed effects. Standard errors are clustered at the zip code level. The sample covers 2013-2020 IRS migration flows and EIA generator retirements.

Figure 6: Fossil-Fuel Generator Retirement and Employment Outcomes: County-Year Analysis



Notes: The figure shows panel event study estimates examining county-year employment outcome surrounding fossil fuel retirements using the entire sample. Retirement year (0) is omitted as the reference. 95% confidence intervals are displayed. This model includes zip, year-quarter, and county-year fixed effects. Standard errors are clustered at the zip code level.

Figure 7: Fossil-Fuel Generator Retirement and Air Quality: County-Year Analysis



Notes: The figure shows panel event study estimates examining county-year level air quality following fossil fuel retirements using the entire sample. Retirement year (0) is omitted as the reference. 95% confidence intervals are displayed. This model includes zip, year-quarter, and county-year fixed effects. Standard errors are clustered at the zip code level.

Appendix: Figures and Tables

Table A1: Summary Statistics for County Characteristics

	Mean Treated	Mean Control	p-value	SMD
Median Household Income	45,646.73	46,840.10	0.013	0.100
Gini Coefficient	0.43	0.43	0.004	0.117
Total Housing Units	42,557.98	35,086.72	0.135	0.060
Average Household Size	2.52	2.55	0.001	0.135
Median Age	40.39	40.15	0.246	0.046
Total Population	99,903.88	82,334.53	0.170	0.055
White Population Ratio	0.84	0.86	0.001	0.133
Capacity (MW)	472.60	655.29	0.000	0.197
Total Generators	7.40	9.11	0.012	0.101
Counties	87	1,744		
Observations	633	23,157		

Notes: This table presents county-level pre-treatment characteristics using 2012 ACS 5-year estimates. It compares means between treated counties containing fossil fuel plant retirements and control counties, with p-values testing differences in means. Standardized mean differences (SMD) are calculated as the difference in means between the two groups, normalized by the pooled standard deviation to assess balance. SMD absolute values below 0.1 or 0.2 indicate negligible differences between the treatment and control groups.

Table A2: Fossil-Fuel Generators Retirement on Migration: County-Year Analysis

	Move In		Move Out		Net Inflow	
	(1)	(2)	(3)	(4)	(5)	(6)
Fossil Fuel Full Retirement	-63.5	-41.3	-148.5***	-87.9	84.9***	46.6
	(55.6)	(71.2)	(47.6)	(65.1)	(32.5)	(32.3)
Outcome mean	2,601	2,601	2,594	2,594	7	7
Observations	23,788	23,788	23,788	23,788	23,788	23,788
Year FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
State-Year FE		✓		✓		✓

Notes: This table presents county-level analysis on the effects of full retirement of fossil-fuel generators on migration. I use IRS data 2013-2020 to conduct the analysis.

Table A3: Impact of Fossil-Fuel Generator Retirement on Migration: Power Plant Buffers

	Baseline			Coarsened Exact Matching (CEM)		
	(1) Move In	(2) Move Out	(3) Net Inflow	(4) Move In	(5) Move Out	(6) Net Inflow
Full retirement of Fossil fuel	-44.234***	-34.452***	9.782	-28.229**	-27.096***	1.133
	(8.370)	(8.355)	(6.387)	(11.036)	(10.241)	(10.152)
Constant	245.028***	232.864***	-12.164***	470.426***	418.211***	-52.215***
	(0.013)	(0.013)	(0.010)	(2.088)	(1.938)	(1.921)
Observations	556672	556672	556672	4016	4016	4016
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Zip fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Use ACS 5-year data(2018) to select covariates: Median household income, Gini coefficient, Total number of housing units, Number of occupied housing units, housing median value, Median gross rent, Median age of the population, Total population, and white ratio.

Table A4: Impact of Fossil-Fuel Generator Retirement on Migration: Percentage COA

(a) Baseline Results

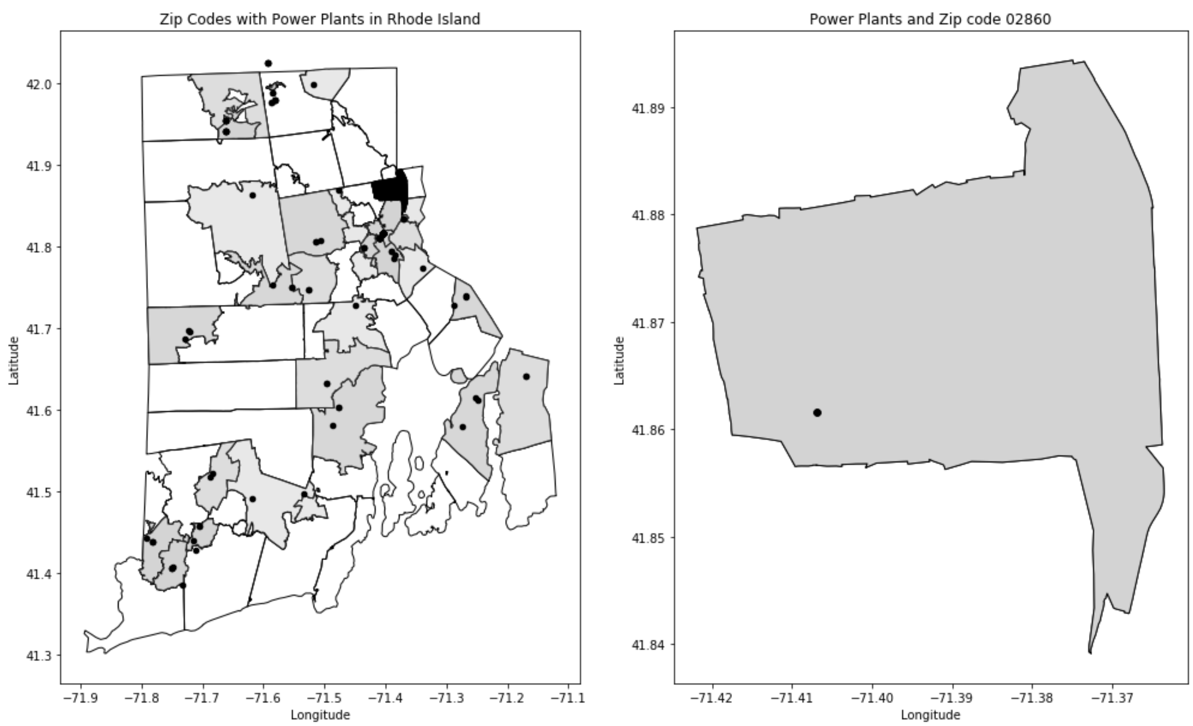
	Baseline			Coarsened Exact Matching (CEM)		
	(1) Move In	(2) Move Out	(3) Net Inflow	(4) Move In	(5) Move Out	(6) Net Inflow
Fossil Fuel Full Retirement	-0.007***	-0.008***	0.006	-0.007**	-0.006**	0.014
	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)	(0.015)
Outcome mean	0.086	0.088	-0.003	0.086	0.088	-0.003
Observations	551,313	550,870	554,689	4,792	4,784	4,826
Year-Quarter FE	✓	✓	✓	✓	✓	✓
Zip FE	✓	✓	✓	✓	✓	✓
County-quarter FE	✓	✓	✓	✓	✓	✓

(b) IV Results

	Baseline			Coarsened Exact Matching (CEM)		
	(1) Move In	(2) Move Out	(3) Net Inflow	(4) Move In	(5) Move Out	(6) Net Inflow
Fossil Fuel Full Retirement	-0.027**	-0.024**	-0.003	-0.012*	-0.010	-0.014
	(0.012)	(0.010)	(0.002)	(0.007)	(0.007)	(0.015)
Outcome mean	0.086	0.088	-0.003	0.086	0.088	-0.003
Observations	551,313	550,870	554,689	4,792	4,784	4,826
Year-Quarter FE	✓	✓	✓	✓	✓	✓
Zip FE	✓	✓	✓	✓	✓	✓
County-quarter FE	✓	✓	✓	✓	✓	✓

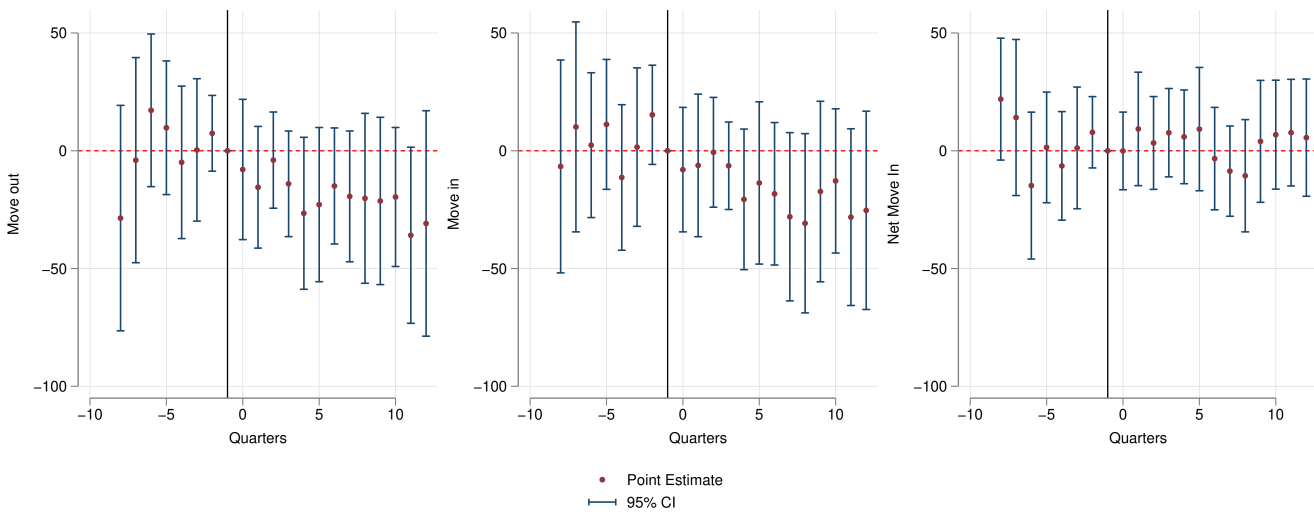
Notes: Use ACS 5-year data(2017) to select covariates: median housing value, total population, lifespan, and the number of generators at the zip code level.

Figure A1: Example of Treatment Indicator for Power Plant Retirement



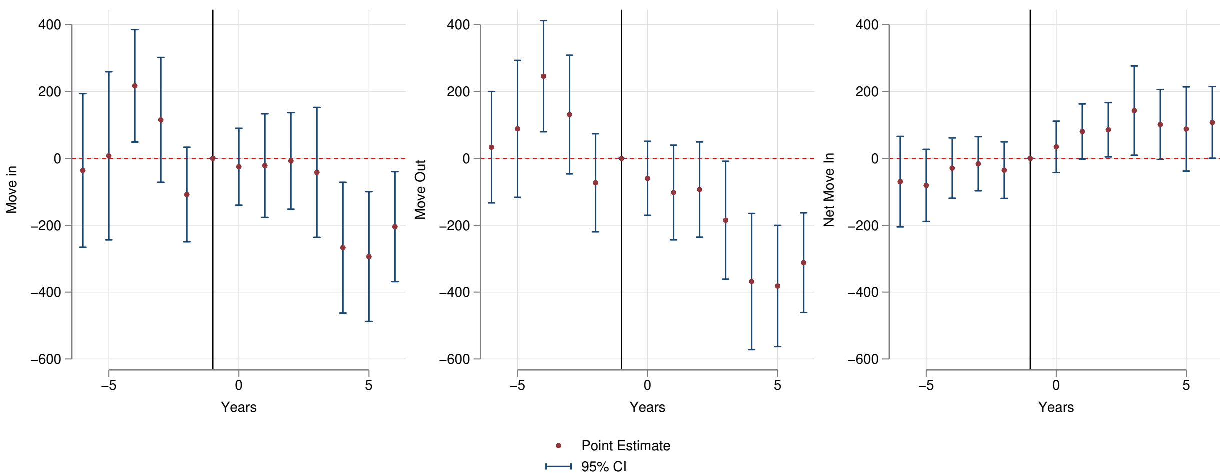
Notes: This figure provides an example of the treatment indicator used to identify zip codes experiencing full retirement of fossil-fuel generators. The left map shows Rhode Island with grey ZIP code areas containing power plants and the black zip code area indicating full fossil fuel retirement. The right map zooms in on the treated zip code 02860 with black dots denoting retired generators at a single power plant location. While two generators retired at this plant, their overlapping location shows as one dot. This treatment indicator is used to estimate the migration impacts of total fossil fuel retirements within a zip code.

Figure A2: Impact of Fossil-Fuel Generator Retirement on Migration: Zip-Quarter Analysis with CEM



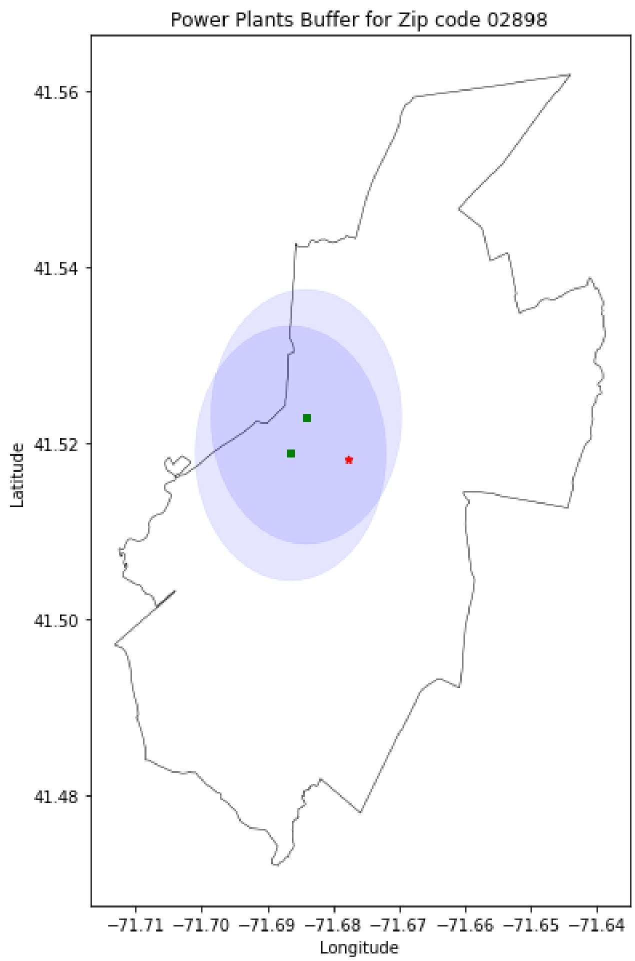
Notes: The figure shows panel event study estimates examining zip code-level migration surrounding fossil fuel retirements using post-matched data. Retirement year (0) is omitted as the reference. 95% confidence intervals are displayed. This model includes zip, year-quarter, and county-year fixed effects. Standard errors are clustered at the zip code level.

Figure A3: Impact of Fossil-Fuel Generator Retirement on Migration: County-Year Analysis



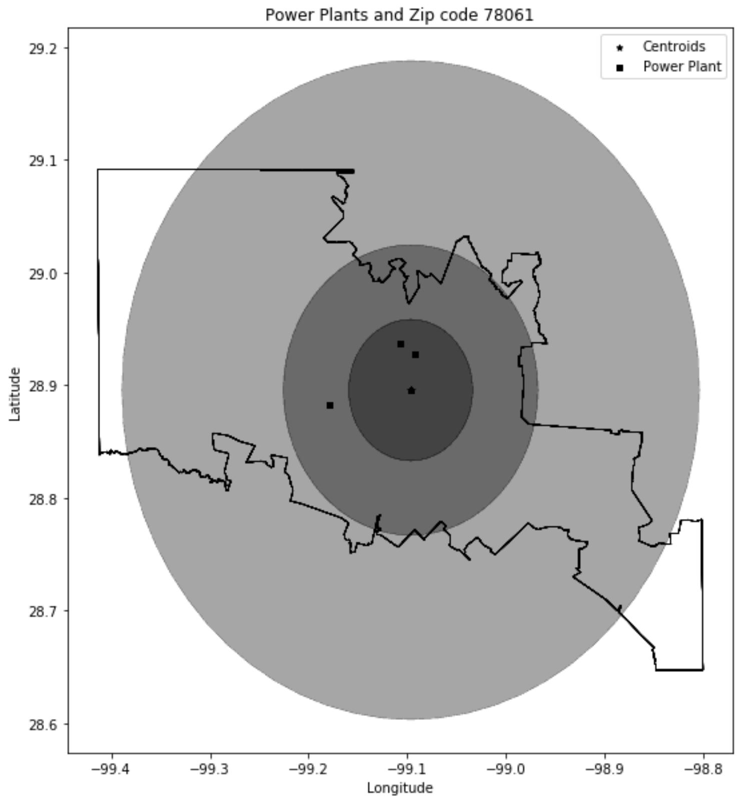
Notes: The figure shows panel event study estimates examining county-level migration surrounding fossil fuel retirements. Retirement year (0) is omitted as the reference. 95% confidence intervals are displayed. This model includes year and county fixed effects. Standard errors are clustered at the county level. The sample covers 2013-2020 IRS migration flows and EIA generator retirements.

Figure A4: Power Plants 2-Mile Buffer Example



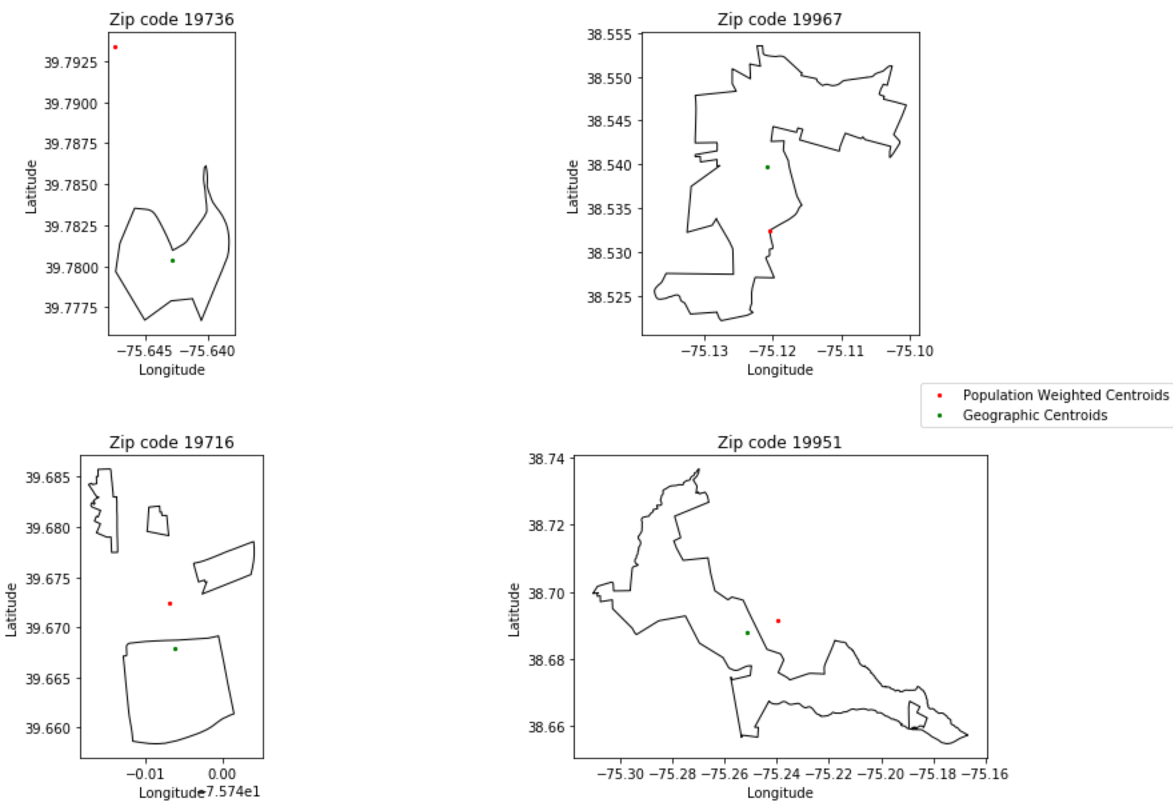
Notes: The figure shows power plants 2-mile buffer for zip code 02898. The red dot is the population-weighted centroid and the green dots indicate the power plant generators. Note that one power plant can have multiple generators, but they will only show on the same latitude and longitude coordinates in the figure.

Figure A5: Zip Code Centroid Buffer Example



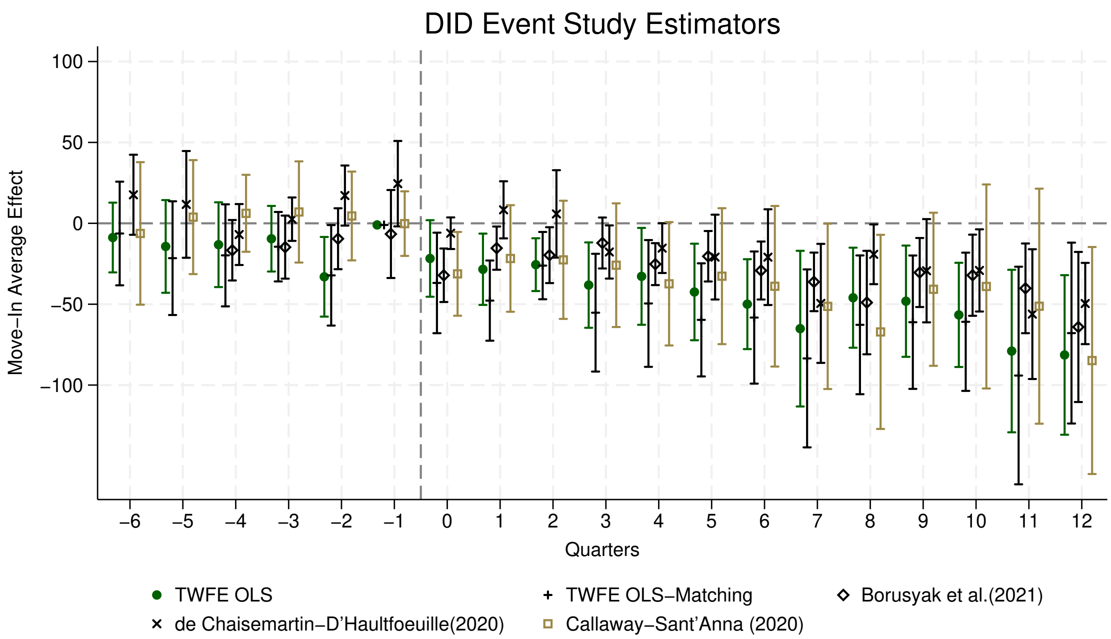
Notes: The figure shows zip code centroid buffer for zip code 78061. Note that one power plant can have multiple generators, but they will only show on the same latitude and longitude coordinates in the figure.

Figure A6: Zip Code Centroids Example



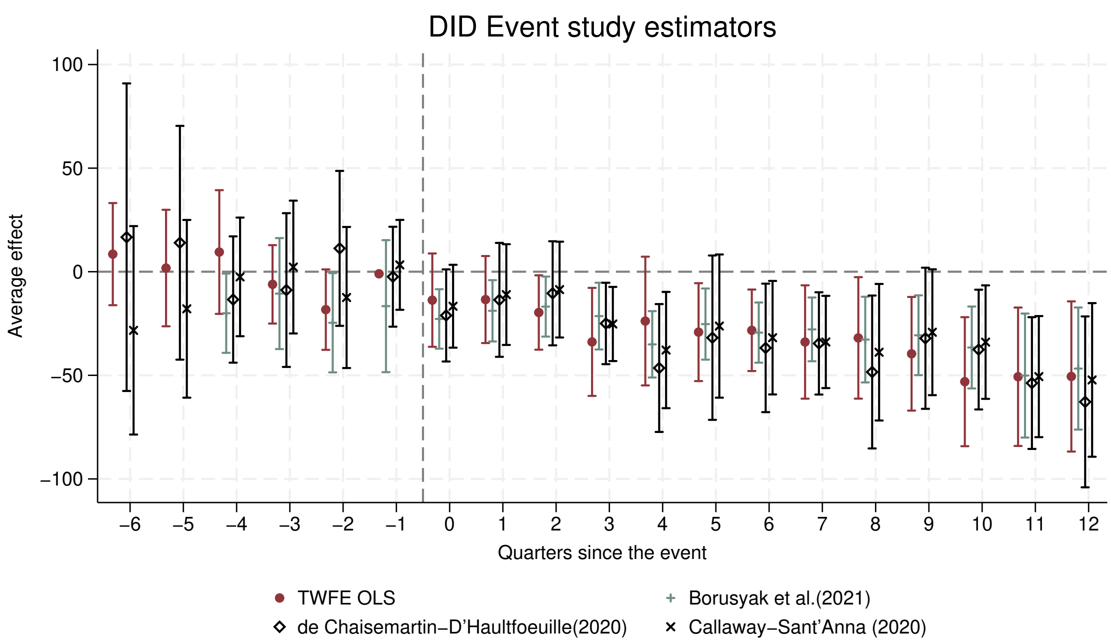
Notes: The figure shows zip code with population weighted centroid and geographic centroid.

Figure A7: Effects of Fossil-Fuel Generator Retirement on Move-In



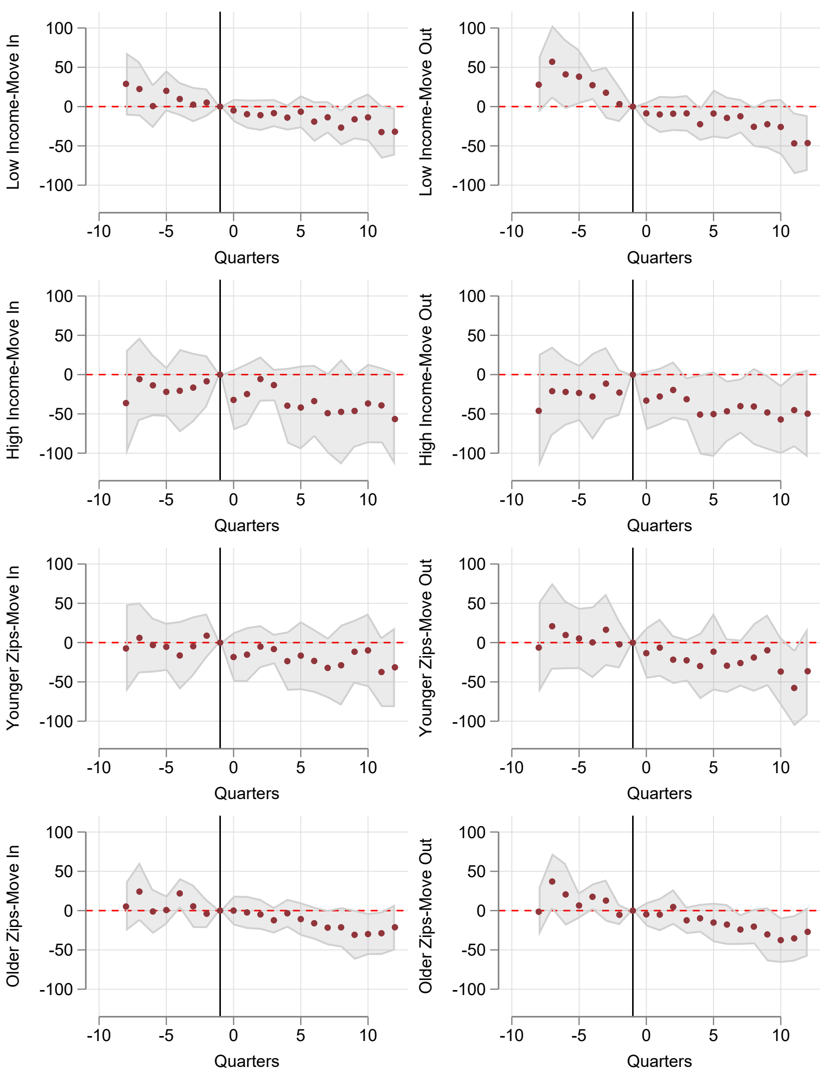
Notes: The figure presents the event-study plots using multiple estimators on move in.

Figure A8: Effects of Fossil-Fuel Generator Retirement on Move-Out



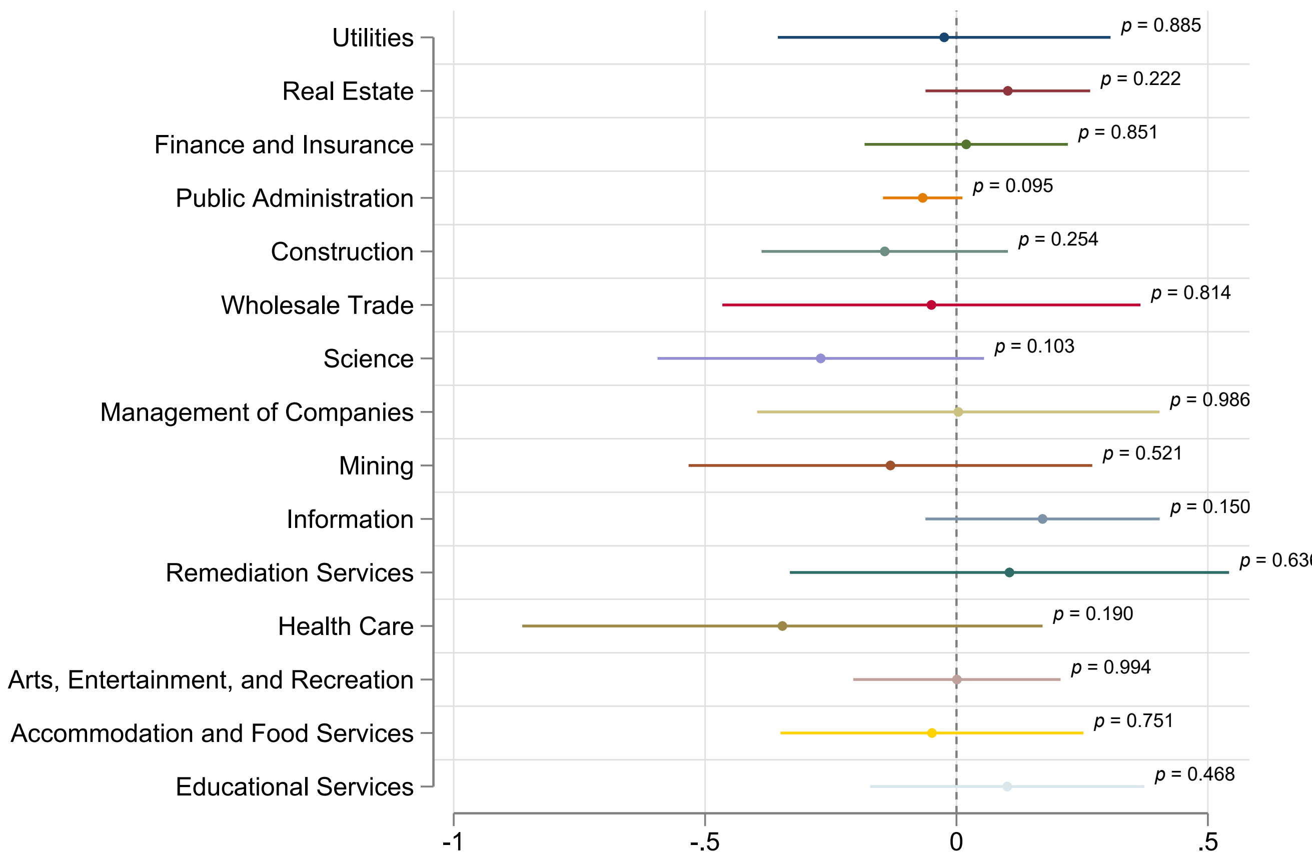
Notes: The figure presents the event-study plots using multiple estimators on move out.

Figure A9: Effects of Fossil-Fuel Generator Retirement on Migration



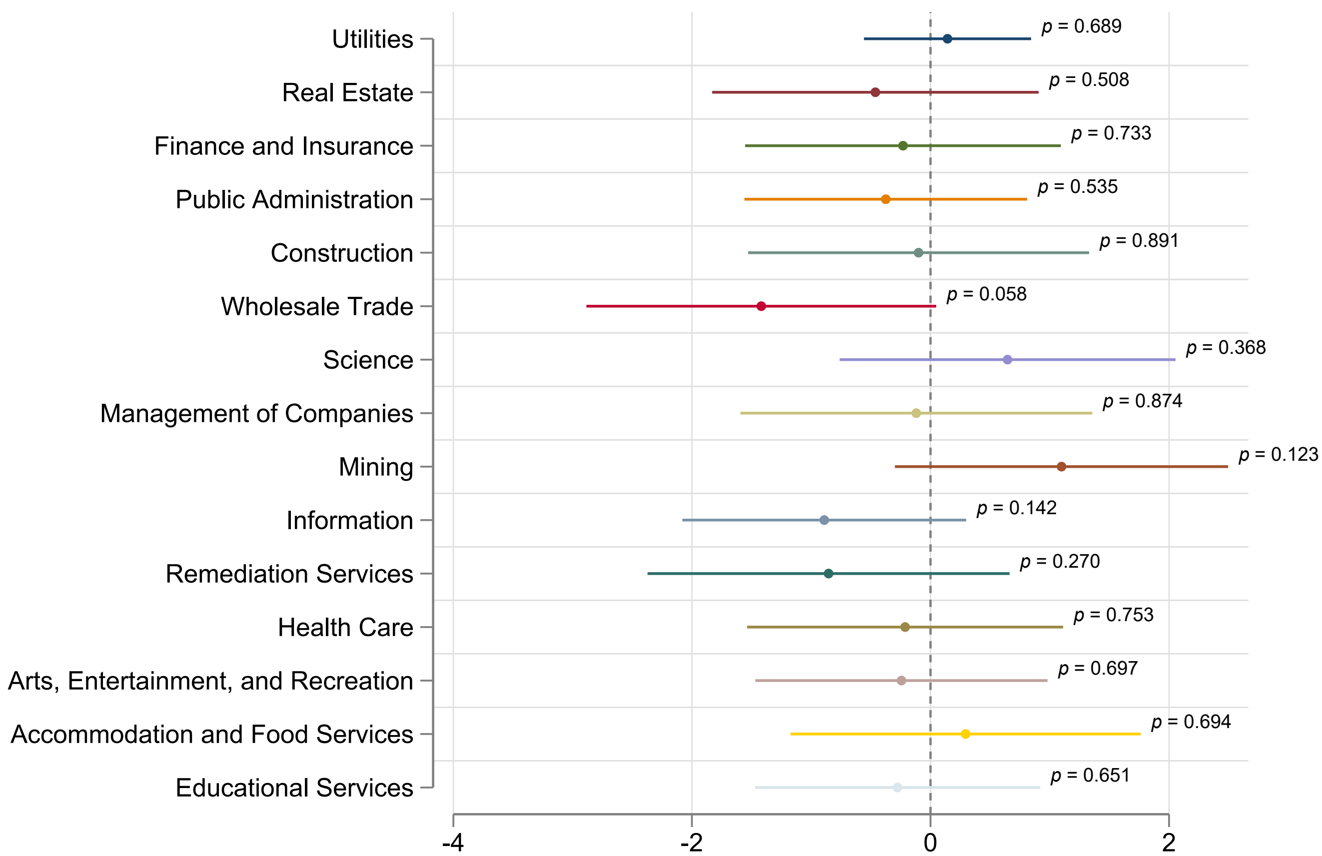
Notes: The figure presents the event-study plots using multiple estimators for different demographic groups.

Figure A10: Effects of Fossil-Fuel Generator Retirement on Log Labor



Notes: The figure presents the estimators of the effects on log labor outcomes.

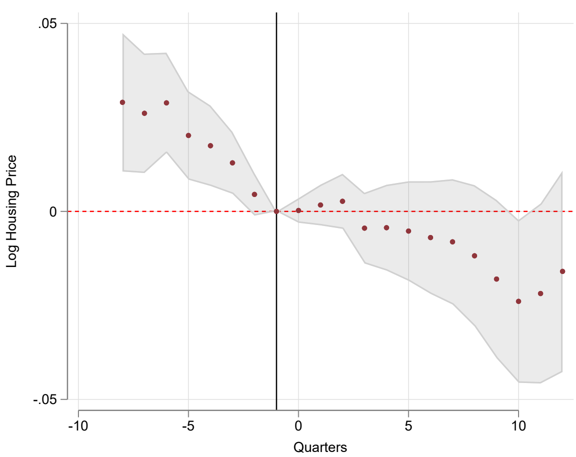
Figure A11: Effects of Fossil-Fuel Generator Retirement on Log First Difference Labor Outcomes



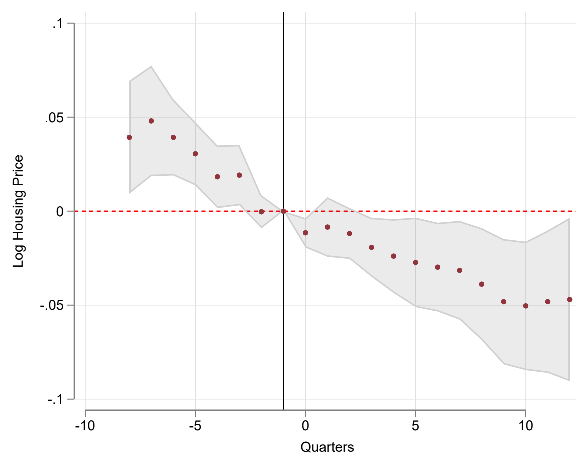
Notes: The figure presents the estimators of the effects on first difference labor outcomes.

Figure A12: Effects of Fossil-Fuel Generator Retirement on Housing Value

(a) Baseline Results



(b) CEM Results



Notes: This figure shows the event study results of full retirement of fossil-fuel generators on housing values in both baseline results and post-matching.