Place-Based Environmental Regulations and Labor Market Dynamics

Ozgen Kiribrahim-Sarikaya

Job Market Paper

Click here for the latest version

Abstract

Place-based environmental regulations target pollution-intensive sectors in polluted areas. These regulations can improve local quality of life by reducing air pollution, while simultaneously reducing labor demand. I develop a framework to study the heterogeneous effects on worker welfare, considering changes in pollution exposure, sectoral and spatial labor distribution, and unemployment. I focus on the U.S. Environmental Protection Agency's regulation of ozone and fine particulate air pollution during the 2000's. First, I develop a triple-difference estimator to measure the employment effects on college-educated and non-college-educated workers. I find that, on average, regulation decreased employment by 7.6% among non-college-educated workers and by 3.6% among college-educated workers. However, these average treatment effects vary substantially depending on the intensity and type of regulation. I use this causal evidence to develop empirical moments that serve to identify key parameters of a new general equilibrium search and matching model with endogenous worker location choice and pollution exposure. I use the model to evaluate the welfare effects of regulation in North Carolina. I find the effects differ by worker skill level and geographic location. Low-skill workers in regulated areas experience notable welfare losses. I show these losses can be mitigated by improving labor mobility across sectors and areas.

JEL: J6, Q52, Q53
Keywords: environmental regulation, air pollution, unemployment, spatial economy

---

Department of Economics, Arizona State University, Email: okiribrahim@asu.edu. *Acknowledgments:* I am extremely grateful to my advisor, Nicolai Kuminoff, and my committee members, Kelly Bishop, Alvin Murphy, and Nicholas Vreugdenhil, for their invaluable comments, guidance, and support. This paper has benefited from helpful discussions with seminar participants at Arizona State University, the AERE 2024 Summer Conference, and the 2024 Western Economics Association Graduate Student Workshop.

1 Introduction

Over the past few decades, governments worldwide have implemented place-based environmental regulations aimed at reducing pollution in heavily polluted places. For example, the United States, China, India, and Mexico all regulate fine particulate air pollution in highly populated areas. These regulations improve human health and labor productivity (Bishop et al. (2023), Deryugina et al. (2019), Aguilar-Gomez et al. (2022)). However, regulations also increase the cost of production (Greenstone et al. (2012), Berman and Bui (2001)), leading to decreased employment and foregone earnings (Walker (2013), Curtis (2018), Greenstone (2002)). The net effect on household welfare depends on how workers sort themselves across polluting and non-polluting sectors in regulated and unregulated places based, in part, on their relative preferences for environmental quality and private consumption.

This paper develops a novel framework to evaluate the distributional welfare impacts of place-based environmental regulations. The framework incorporates endogenous changes in pollution exposure and worker allocation across employment status, sectors, and regions. I use the framework to examine the implementation of the National Ambient Air Quality Standards (NAAQS) set by the U.S. Environmental Protection Agency (EPA) to regulate air pollution in the United States. The NAAQS establish maximum limits on human exposure to harmful air pollutants. The EPA enforces these regulations by targeting pollution-intensive sectors in counties where pollution levels exceed the standards.

I focus on the 1997 revisions to the NAAQS, for which the EPA lowered the maximum limit on ozone pollution and introduced a new standard for fine particulate matter ($PM_{2.5}$). The EPA designated counties that exceeded the new ozone limit as "nonattainment" in 2004, targeting them for enhanced regulation. Some of these same counties were also regulated for $PM_{2.5}$ the following year. Additionally, some counties were designated solely as nonattainment for $PM_{2.5}$. The 1997 revisions generated plausibly exogenous variation across time and space as polluting sectors were regulated in newly affected counties.

My analysis starts by providing evidence on the causal effect of regulation on employment. I use Quarterly Workforce Indicators data and a triple difference-in-differences estimator that accommodates heterogeneity in the timing and intensity of enforcement (Callaway and Sant'Anna (2021), De Chaisemartin and D'haultfœuille (2023)). My econometric design incorporates multiple regulatory treatments, variation in treatment timing, and multiple time periods. It identifies the heterogeneous effects of regulation on employment among college-educated and non-college-educated workers in polluting sectors of newly regulated counties.

I find that the regulatory expansion led to a 7.6% decrease in employment among non-college-educated workers. In contrast, I find that employment for college-educated workers declined by 3.6%, although this result is not statistically distinguishable from zero. The impact of the regulations varies with the type of pollutant and the intensity of enforcement. Specifically, regulations targeting either ozone or $PM_{2.5}$ alone did not have a significant effect on college-educated employment, but when both regulations were implemented together, college employment fell by 15% seven years after designation. In contrast, non-college employment experienced substantial declines, with employment decreasing by 12% due to ozone regulations, 17% due to $PM_{2.5}$ regulations, and 11% in areas where both were enforced. The combined effect of both regulations may be smaller than the average effect of each regulation individually because the effects are derived from different treatment groups. Overall, these results suggest that the intensity of regulatory enforcement plays a key role in shaping employment outcomes.

This causal evidence suggests that environmental regulation *might have* reduced welfare for some workers in the regulated areas because of job losses. However, measuring the welfare effects of regulation requires accounting for various other factors that are not easily identifiable through a regression-based design. These include the regulation's indirect effects on employment in unregulated sectors and areas, worker flows between employment and unemployment, worker movement across regulated and unregulated sectors, worker movement across geographic areas, and any associated changes in housing prices, wages, and pollution exposure.

To evaluate the distributional welfare effects of regulation, I develop a general equilibrium search and matching model that incorporates labor market frictions, the spatial and sectoral distribution of the labor force, and endogenous pollution exposure. The model combines elements of the search and matching framework from the Diamond-Mortensen-Pissarides model (Pissarides (2000)) with features of spatial equilibrium models (Rosen (1979), Roback (1982), Kline and Moretti (2013)). I account for endogenous pollution exposure and the movement of local air pollutants by incorporating an integrated assessment model of atmospheric transport.[1]

The resulting model depicts local labor markets that vary in both productivity and amenities. Each location has two sectors—clean and dirty—that produce sector-specific goods using college-educated and non-college-educated labor. Firms in both sectors post job vacancies for each skill type, but only the dirty sector emits air pollution. Workers differ by educational attainment and derive utility from local amenities (including air quality), housing, and consumption of a composite good produced from both clean and dirty sector products. They can be either employed or unemployed, and those who are unemployed choose where to live and search for jobs. Once matched with a job, employed workers supply a unit of labor inelastically and earn wages specific to the sector and location. The government enforces a performance standard to limit emissions from the dirty sector in high-pollution areas so that regulated sectors face abatement costs per unit of output.

This framework allows regulations to affect the local labor market through two main channels. First, abatement costs can reduce net output per worker, decreasing the value of filling vacant positions. As a result, fewer vacancies are posted by regulated, polluting sectors, and job-finding rates decrease in those sectors. Second, regulations can improve air quality, both in regulated and nearby unregulated areas, as pollution disperses across the spatial landscape. Together, these channels shape the spatial and sectoral distribution of labor, influencing unemployment rates,

[1] The Air Pollution Emission Experiments and Policy Version 3 (AP3) model links emissions from five key criteria air pollutants to $PM_{2.5}$ exposures, physical impacts, and associated monetary damages across the contiguous United States at the county level (Muller and Mendelsohn, 2007, 2009; Muller et al., 2011).

sector-specific employment, migration, and welfare.

I use the model to evaluate the welfare effects of regulation in the state of North Carolina. First, I calibrate the model to replicate sectoral employment shares, relative wage differences, and unemployment rates by worker skill in each of North Carolina's 21 commuting zones (CZ) before the 1997 regulatory standards. I define a commuting zone to be regulated if any county within it was regulated. Then, I use my reduced-form estimates for the causal effect of regulation on employment to calibrate empirical latent abatement rates for ozone and $PM_{2.5}$. Finally, I use the calibrated model to evaluate the effect of the 1997 Standards on sectoral employment by skill, unemployment, dirty-sector production, local amenities, and labor reallocation across sectors and zones.

The welfare effects differ for low- and high-skill workers in regulated and unregulated CZs. Low-skill workers in regulated CZs experience a welfare loss of 1.38%, with this loss rising to 2.39% in CZs specifically regulated for $PM_{2.5}$. This suggests that stricter regulation is associated with greater welfare reductions because I find that dirty sectors in $PM_{2.5}$-regulated CZs had higher emission abatement rates. In unregulated CZs, the welfare of low-skill workers improves by 1.46%. For high-skill workers, welfare generally improves in regulated CZs due to reduced pollution. In contrast, welfare declines for high-skill workers in unregulated CZs because those CZs experience an increase in dirty sector production and air pollution.

To understand the forces driving the welfare effects, I use the model to measure the underlying changes in employment, amenities, and dirty sector production. My findings suggest that the 1997 standards reduced low-skill employment within dirty sectors of regulated CZs by 8.58%. This decline was partially offset by a 1.41% increase in clean sector jobs. Despite improvements in amenities within regulated CZs, the reduction of job opportunities in the dirty sector led low-skill workers to migrate to unregulated CZs where dirty sector jobs were more abundant. Unregulated commuting zones experienced spillover effects, with a 4.97% increase in dirty sector employment and a 1.15% increase in clean sector employment as low-skill workers moved from regulated CZs. Taken together, these results suggest that the regulation's effect on low-skill dirty sector employment may have been considerably smaller than my reduced-form estimates for the relative treatment effect on workers in polluting sectors of regulated counties due to endogenous labor reallocation.

For high-skill workers, my results suggest that regulation increased employment in both sectors for most regulated CZs. My results also show that high-skill workers were more likely to relocate to regulated CZs, as their pollution declined relative to unregulated CZs. This is partly driven by a shift in dirty sector production to unregulated CZs.

To further investigate the role of labor mobility in mitigating negative welfare effects, I simulate the model under two counterfactual scenarios that shut down channels for labor mobility. Without spatial mobility, the welfare of low-skill workers decreases by 3.47%, and it drops even further by 9.58% when both spatial and sectoral mobility are restricted. These restrictions hinder the reallocation of low-skill workers and increase unemployment. As a baseline for comparison, low-skill unemployment rates in regulated CZs rose slightly (0.05 percentage points) under the "free mobility" case. The increase was substantially higher in each of the restricted mobility scenarios, reaching 0.76 percentage points with no residential mobility and 1.77 pp when workers are also prohibited from switching between the clean and dirty sectors.

Overall, this counterfactual analysis illustrates that place-based environmental regulations can produce uneven welfare impacts, with the ability to relocate or shift sectors significantly influencing worker welfare. For low-skill workers, in particular, the negative welfare impacts of place-based regulation can be reduced substantially by moving across commuting zones and sectors. Thus, my findings suggest that policies that increase labor mobility across sectors and/or space can substantially offset the negative welfare effects of regulations.

Related Literature

Overall, this paper advances the literature in three ways. First, I provide novel evidence that non-college-educated workers in the regulated sector are more likely to experience a decrease in employment due to regulation. Walker (2011), Curtis (2020), and Curtis (2018) estimated the overall impacts of regulating air pollution on employment in the regulated sectors. My work reveals how these impacts vary with worker skill. In addition, this paper is the first to document the effect of $PM_{2.5}$ regulation on employment. I also identify the heterogeneous effects of treatment intensity by leveraging recent advances in econometric design and demonstrate how regulations on different air pollutants interact to affect employment outcomes for college and non-college graduates.

Second, my general equilibrium model provides a unified framework to evaluate the welfare effects of place-based policies that simultaneously affect local amenities and labor market outcomes. Prior general equilibrium studies of environmental regulation mainly focused on the implications of implementing a nationwide carbon tax (Hafstead and Williams III (2018), Fernández Intriago (2019), Hafstead et al. (2022), Aubert and Chiroleu-Assouline (2019), Balistreri (2002), Shimer (2013)). My framework complements this work by adding two important dimensions: spatial labor mobility and changes in amenity exposure. These features offer the potential to improve our current understanding of the impacts of spatially heterogeneous regulation of other primary air pollutants like ozone and $PM_{2.5}$. Another strand of the recent GE literature uses spatial models to examine the consequences of environmental regulations (Rudik et al. (2022), Hollingsworth et al. (2024), Morehouse (2021), Aldeco et al. (2019)). In contrast to my work, these studies rely on a full-employment assumption and abstract from heterogeneity in worker skill and the effects of regulation on involuntary unemployment.[2] My framework goes beyond analyzing wages to investigate how worker welfare is affected by the impacts of regulation on unemployment and job-finding rates. My findings indicate that mobility constraints across different sectors or regions greatly impact the unemployment rate for low-skilled workers.

Finally, my framework examines the distributional effects of environmental regulations on low- and high-skill workers, identifying which group is more likely to bear the costs or reap the benefits of these policies. Low-skill workers in regulated zones experience welfare losses due to reduced dirty sector employment, though mobility can help mitigate these losses by providing access to alternative

[2]Hollingsworth et al. (2024) incorporates the choice of remaining non-employed; however, this captures the impact on worker transitions out of the labor force.

job opportunities. In contrast, high-skill workers benefit from welfare gains in regulated zones, largely due to improved amenities. Differences in mobility between high- and low-skill workers can either widen or narrow the gap in welfare outcomes, influencing how each group adapts to regulatory changes.

The remainder of the paper is organized as follows: Section 2 outlines the key institutional features of the National Ambient Air Quality Standards and the 1997 revision to the standards. Section 3 describes the data used in the analysis. Section 4 details my empirical design and presents results from my reduced-form analysis. Section 5 introduces the theoretical model for quantitative analysis. Section 6 discusses the calibration strategy and assesses model fit. Section 7 reports my estimate for how regulation on affected workers in North Carolina. Finally, Section 8 concludes.

2 Background

The Clean Air Act (CAA) of 1963 was a milestone in the history of environmental regulation in the United States. It aimed to limit emissions of air pollutants to protect public health and environmental quality. The CAA was amended several times. The 1970 Amendments empowered The Environmental Protection Agency (EPA) to set the National Ambient Air Quality Standards (NAAQS), which specify the maximum allowable ambient concentration of six criteria air pollutants: Particulate Matter, Carbon Monoxide, Nitrogen Oxides, Sulfur Dioxide, Lead, and Ozone.

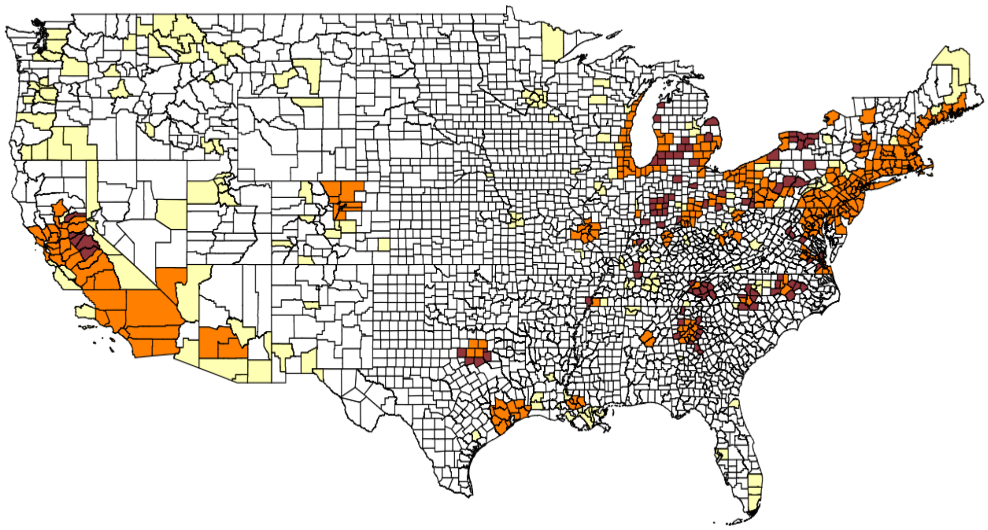
The 1977 CAA Amendments empowered the EPA to designate every county as either "attainment" or "nonattainment" for each pollutant annually, based on whether the county's maximum concentration exceeds the NAAQS. When a county is designated as nonattainment, the state must develop a State Implementation Plan (SIP) to reduce the county's emissions below the NAAQS. SIPs usually impose specific regulations on individual plants, mandating that existing polluting facilities adopt the lowest achievable emission rate technologies, irrespective of cost.[3] Moreover, any new emissions from plant operations, whether due to new construction or expansion, must be counterbalanced by reductions from other sources within the same county. The 1990 Amendments further mandated that major sources of air pollutants must obtain an operating permit under the Title V Operating Permit Program, regardless of location.

These regulations raise production costs for polluting plants in nonattainment counties compared to those in attainment counties. Nonattainment counties have experienced declines in their number of establishments and new plant openings (Curtis (2020), Becker and Henderson (2000)). Additionally, county regulatory status can affect the location decisions of new polluting plants, resulting in long-term spatial reallocation of polluting sectors from nonattainment to attainment counties (Henderson (1996)).

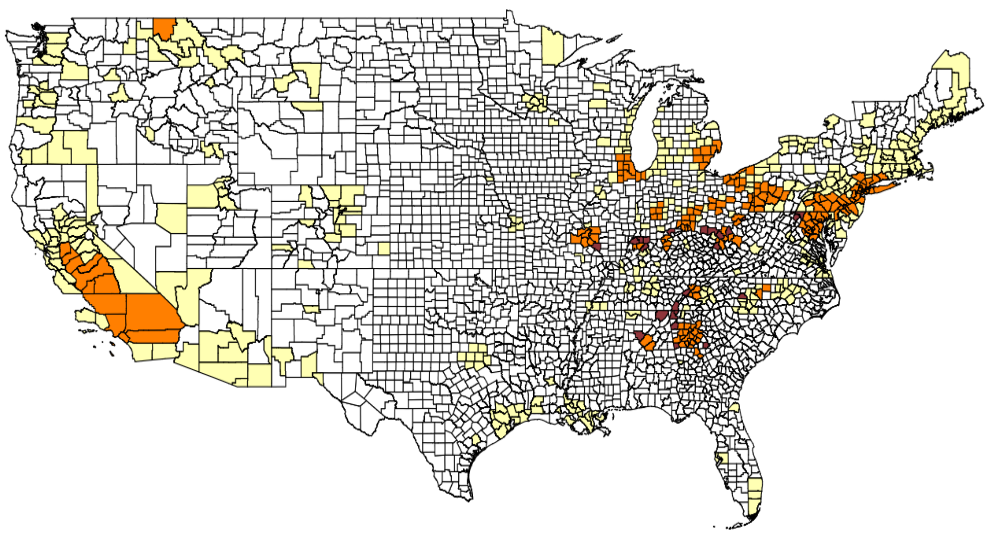
My analysis focuses on a recent revision to the NAAQS for ozone and particulate matter. In 1997, the EPA tightened the ozone standards, causing 434 counties to be classified as nonattainment

[3] Since the 1977 Amendments, large polluting plants in attainment counties are required to adopt the less costly best available control technology (BACT), while plants in nonattainment areas face stricter regulations, higher abatement, and operating costs, and more frequent inspections (Becker (2005), Becker and Henderson (2001)).

Figure 1: County Regulatory Status



(a) 1992-2004



(b) 1992-2005

Note: The top figure (Panel 1a) shows counties designated as nonattainment at some point between 1992 and 2004, including those regulated for the 1997 ozone standards in 2004. Noncolored counties are attainment areas. Light yellow counties were regulated for other pollutants during this period. Orange and maroon counties represent nonattainment areas for the 1997 ozone standards in 2004, with maroon counties switching from attainment to nonattainment for the first time in 2004. The bottom figure (Panel 1b) shows counties designated as nonattainment from 1992 to 2005, along with counties regulated for the 1997 $PM_{2.5}$ standards in 2005. Noncolored counties are attainment areas, and light yellow counties were regulated for other pollutants during this period. Orange and maroon counties represent nonattainment areas for the 1997 $PM_{2.5}$ standards in 2005, with maroon counties switching to nonattainment for the first time in 2005.

on July 15, 2004.[4] Within this set, 98 counties entered nonattainment status for the first time, while 327 were already out of attainment with the previous ozone standard.[5] Figure 1a displays counties classified as nonattainment at any point between 1992 and 2004. Counties highlighted in orange and maroon were regulated for ozone in 2004. The orange counties were regulated for ozone prior to 2004, whereas the maroon counties switched from attainment to nonattainment for the first time in 2004.

Additionally, on April 5, 2005, 208 counties were designated as nonattainment for the new $PM_{2.5}$ standards. However, only 23 of these counties entered nonattainment status for the first time. Further, 24 of the counties that were first regulated for ozone in 2004 also exceeded the $PM_{2.5}$ standards in 2005 and became regulated for both pollutants.[6] Figure 1b highlights counties classified as nonattainment at any point between 1992 and 2005. The counties marked in orange and maroon were regulated for $PM_{2.5}$ in 2005, and the maroon counties switched from attainment to nonattainment for the first time in 2005.

Together, Figures 1a and 1b show how the 1997 revisions to the NAAQS created three sources of variation in place-based environmental regulation. The first source of variation is temporal. Some counties switched from attainment to nonattainment for the first time. This variation allows me to make before-after comparisons within county-industry pairs while accounting for their time-invariant unobserved characteristics. The second source of variation is geographic, as attainment status varies across space in any given year. This allows for comparisons between county-industry pairs while controlling for nationwide or sector-specific shocks, such as the Great Recession in 2008. The final source of variation arises from plant-level differences within the same county. Only the plants that emit the regulated pollutant are subjected to new regulations due to the change in the county's regulatory status of that pollutant. This allows for comparisons between polluting and nonpolluting sectors while controlling for unobservable county-by-sector characteristics. These sources of variation contribute to a research design, outlined in Section 4, that investigates the employment outcomes of workers in the polluting sectors of newly regulated counties, comparing results before and after the regulations were implemented.

3 Data Sources

This section outlines the key data sources used in this paper. These sources enable a comprehensive assessment of air pollution, regulatory status, and local labor market conditions.

The EPA's Green Book and AirNow Files

The EPA's Green Book reports each county's annual attainment status for each criteria pollutant.

[4]Prior to 1997, the ozone standard was 0.12 parts per million (ppm) over a 1-hour average concentration. The EPA set the new standards at 0.08 ppm over an 8-hour average in 1997.

[5]336 of them were in attainment for the previous standards of different criteria air pollutants. See `https://www3.epa.gov/airquality/greenbook/gbtcw.html` for 8-Hour Ozone (1997) Designated Area/State Information.

[6]161 regulated counties were in attainment for the previous standards of different criteria air pollutants. See `https://www3.epa.gov/airquality/greenbook/qbtcw.html` for $PM_{2.5}$ (1997) Designated Area/State Information.

I use these data to track the duration of each county's regulatory status for each criteria pollutant following the 1997 NAAQS changes. These data underlie the maps of counties that are first-time switchers into nonattainment status for ozone and/or $PM_{2.5}$ in Figure 1a and Figure 1b.

To define a set of attainment counties to be used as the control group in my analysis, I employ the EPA's AirNow files, which report the annual concentrations of air pollutants at outdoor monitoring status across the US. Roughly one-third of US counties have outdoor monitors.[7] However, these monitored counties account for 83% of the US population. This is because monitors tend to be placed in areas with relatively high populations and/or areas that are believed to have relatively higher pollutant concentrations.[8] Counties lacking monitors are technically classified as attainment counties, but it is standard in the literature to exclude them from regression analyses because their pollution levels are not precisely measured, and they tend to be less populated rural areas that are less appropriate as controls (e.g. Bishop et al. (2023)).

The EPA's Air Facility Subsystem (AFS)

I use the EPA's Air Facility Subsystem database to identify the polluting sectors in each county. The AFS provides plant-level information on the specific pollutants covered by the plant's operating permit and the corresponding regulatory program for which the permit is issued. However, the date of permit issuance is not available. Fortunately, the CAA's regulatory structure enables me to infer the missing information. For example, suppose a plant within a nonattainment county for $PM_{2.5}$ receives a $PM_{2.5}$ permit, and the associated regulatory program is identified as the *CAA State Implementation Plan*. It logically follows that the plant obtained the permit after the county transitioned into nonattainment status. Thus, by examining county nonattainment status alongside the corresponding regulatory programs, I can infer the timing of regulatory interventions.[9] To focus on the impact of the 1997 CAA Expansion on employment in regulated sectors, I limited the sample to plants holding permits for emissions that contribute to ozone and/or $PM_{2.5}$.[10] Lastly, I aggregate the plant-level data into sector-level categories using three-digit NAICS codes following Greenstone (2002), Kahn and Mansur (2013) and Curtis (2020).

The Quarterly Workforce Indicators (QWI)

The Quarterly Workforce Indicators (QWI) provide detailed information on local labor market conditions by county, industry, and worker demographics. The primary underlying source file is the Longitudinal Employer-Household Dynamics (LEHD) dataset, which links employers to employees, covering over 95% of U.S. private sector jobs. This linkage enables the QWI to provide labor market

[7]Figure 10 in Appendix A.I the counties with outdoor monitors in the US.

[8]See for details about the placement of outdoor monitors.

[9]To classify a plant as regulated, I followed the criteria outlined by Walker (2013). A plant is considered regulated if it holds any of the following permits within the Air Program Code field of the AFS database: Title V Permit, State Implementation Plan (SIP) Source, SIP Source under federal jurisdiction, Prevention of Significant Deterioration (PSD) permit, New Source Review (NSR) permit, or New Source Performance Standards (NSPS) permit.

[10]Ground-level ozone is created through the interaction of volatile organic compounds (VOC) and nitrogen oxides (NOx). Hence, plants holding operating permits for VOCs and/or NOx are defined as polluters of ozone. Table 7 in Appendix A.II shows the percentage of permits held by sectors in the estimation sample and the U.S.

data by worker age, sex, educational attainment, and race/ethnicity, allowing for demographic-specific analysis within labor markets or industries. Moreover, the QWI uses worker-firm links to track worker flows, including hiring and separation rates by industry. I aggregate the quarterly data into annual figures for employment, earnings, hiring, and separation rates, categorized by county, NAICS 3-digit sector, and worker education level.[11]

The 2000 U.S. Census

I use the 5 percent sample of the 2000 U.S. Census from the Integrated Public Use Microdata Series (IPUMS) to construct estimates of population, labor force distribution by education level, and housing rents at the commuting zone level. The data provide individual-level information on a wide range of demographic and economic characteristics for over 14 million individuals in the U.S., including labor force status, education level, age, housing costs, and housing characteristics. The lowest level of geography identified in the 2000 Census is the Public Use Microdata Area (PUMA) level. I use a crosswalk from PUMAs to counties to aggregate the microdata to the commuting zone level, which is the geographic unit of analysis in Section 6.[12]

Current Population Survey

I construct worker flows by sector and education level using data from the Current Population Survey (CPS). Although the CPS reports data at the county level, its limited sample size makes it challenging to identify many counties. To address this, I use data from metropolitan statistical areas (MSAs) that correspond to the commuting zones of interest.[13] I average the monthly worker flow rates from 1998 to 2003 to enhance the accuracy of the estimates and then convert them to a yearly frequency. Additionally, I gather data on average weekly hours worked at the sector-education level.

National Emission Inventory

The EPA's National Emissions Inventory (NEI) provides data on air pollution emissions from all sources at the county-sector level. I use data from the NEI on emissions of precursors to $PM_{2.5}$ and ozone, focusing on point and area sources in 2001.[14] I restrict the sample to emissions from the manufacturing sectors by using detailed information on source classification codes (SCC) and industry classification codes (6-digit NAICS) available in the NEI files.

Finally, I gather information on local sectoral economic activity from the Bureau of Economic

[11]The length of QWI longitudinal data varies by state. I use data from the forty-three states whose data go back to at least 2001. The states excluded are Alaska, Arizona, Arkansas, Hawaii, Massachusetts, Mississippi, and New Hampshire. In addition, The District of Columbia and the US territories are excluded. Furthermore, I excluded the county-sector pairs with observations less than four quarters of a given year.

[12]Please see Appendix A.III for the matching of PUMAs in the 2000 U.S. Census to the 2000 Commuting Zones, following Dorn (2009).

[13]Kuhn et al. (2021) demonstrate that worker flows and unemployment rates at the CZ and MSA levels exhibit similar trends.

[14]The precursors to $PM_{2.5}$ and ozone, which are also utilized in the Air Pollution Emission Experiments and Policy Version 3 (AP3) model, include ammonia (NH_3), nitrogen oxides (NO_x), fine particulate matter ($PM_{2.5}$), sulfur dioxide (SO_2), and volatile organic compounds (VOCs) (Muller and Mendelsohn (2009), Muller et al. (2011)).

Analysis (BEA) Regional Economic Accounts. This data provides sectoral payroll information and GDP per worker at the county level.

4 Causal Evidence on Employment Effects of Regulation

I estimate how the 1997 expansion of ozone and $PM_{2.5}$ standards affected the employment outcomes of different education groups in regulated sectors of nonattainment counties. This requires accounting for observed and unobserved differences at sectoral and county levels. I control for these potential confounders by developing a triple-difference design.

Institutional features of the 1997 CAA Expansion may cause treatment effects to be heterogeneous across groups and across time, presenting well-known econometric challenges. As explained in section 2, the timing for Ozone and $PM_{2.5}$ regulations differed, which could lead to heterogeneous treatment effects.[15] Further, some sector-county pairs are subject to regulation under both the ozone and $PM_{2.5}$ standards, resulting in multiple treatments with variation in treatment timing. This raises a potential concern that one treatment may contaminate estimates for the effect of the other. Overall, these institutional features make it crucial to allow for heterogeneous treatment effects in a way that mitigates the various threats to causal inference.

These econometric issues have been addressed for the context of the canonical difference-in-differences and two-way fixed effect estimators (Roth et al. (2023), Borusyak et al. (2021), De Chaisemartin and d'Haultfoeuille (2020), Sun and Abraham (2021), Goodman-Bacon (2021), Callaway and Sant'Anna (2021), Athey and Imbens (2022)). In contrast, their implications for triple difference (DDD) estimation have received much attention (Borusyak et al. (2021), De Chaisemartin and d'Haultfoeuille (2024)).[16] Therefore, I extend the work of Callaway and Sant'Anna (2021) and De Chaisemartin and D'haultfœuille (2023) to the DDD setting to develop an estimator that accounts for multiple time periods, variations in treatment timing, and several treatments. My empirical strategy is based on the potential outcomes framework and aims to identify the group-time average treatment effect. Specifically, I aim to answer the following questions: (i) What is the average treatment effect of regulation on the treated? (ii) What is the treatment effect of ozone and/or $PM_{2.5}$ regulation on the treated? (iii) How do treatment effects vary with treatment duration?

4.1 Empirical Framework

I consider 11 years, $t \in \{2001,....,2011\}$ and n sectors i=1,....,n. My primary goal is to identify group-time average treatment effects, where a group, g, is defined by the first time sector i is

[15] In the presence of heterogeneous treatment effects, the parameter of interest would be a potentially non-convex weighted average of the parameters of each group, and weights could be negative for some groups. This also may present a concern with multiple time periods if treatment effects vary across time. See Roth et al. (2023) for a comprehensive literature review.

[16] Sant'Anna also discusses extending the difference-in-differences framework, presented in Callaway and Sant'Anna (2021), into a triple difference setup in Sant'Anna (2023).

treated. Though regulations are imposed at the county level, they apply selectively to sectors. Only the sectors classified as "polluting" for a particular pollutant in nonattainment counties are regulated. Thus, classification into treatment groups depends on both the county's regulatory status for a pollutant and the sector's classification as a polluter.

I examine two binary treatments: ozone and $PM_{2.5}$ standards. For each sector i, $g_i = (g_{i,1}, g_{i,2}) \in \{0, 2004\} \times \{0, 2005\}$ denotes when sector i was first regulated for ozone and $PM_{2.5}$, respectively. The vector g can take four distinct values, namely $g \in \{$ (2004,0), (0,2005), (2004,2005) (0,0)$\}$, where, for example, $g =$ (2004,0) denotes sectors treated for ozone starting in 2004 but never treated for $PM_{2.5}$. By grouping sectors into these four categories, I can analyze the impact of each treatment independently and in combination.

County regulatory status is denoted by $C = (c_1, c_2)$. Here, $c_1 \in \{0, 2004\}$ indicates when a county is first regulated for ozone and $c_2 \in \{0, 2005\}$ indicates when a county is first regulated for $PM_{2.5}$. Within each set of counties, sectors are partitioned into polluting (P) and non-polluting (NP) groups for ozone and $PM_{2.5}$, denoted by $\mathcal{L} \in \{P, NP\}$. The partition P includes sectors identified as polluting for Ozone, $PM_{2.5}$, or both, whereas NP includes sectors classified as non-polluting for either or both pollutants. To clarify the notational distinction between c and g, consider a simple example: Sector i belongs to the group treated only for ozone, $g = (2004, 0)$ if and only if the regulatory status of the county to which sector i belongs is $C = g = (2004, 0)$ and sector i falls into partition $\mathcal{L} = P$ for ozone. If sector j in the same county is only classified as a polluter of $PM_{2.5}$, despite having $C = (2004, 0)$, unit j would not be considered as belonging to $g = (2004, 0)$ since $\mathcal{L} = NP$ for ozone.

To define the average treatment effect on the treated, let $Y_{i,t}(g)$ be the potential outcome for sector i at time t in group g. Specifically, $Y_{i,t}(g)$ equals the log of employment either for workers with a college degree or higher or for those with a high school diploma or lower. The group-time average treatment effects for g, ATT(g,t) is defined:

$$ATT(g, t) = \mathrm{E}[Y_t(g_1, g_2)|C = g, \mathcal{L} = P] - \mathrm{E}[Y_t(0, 0)|C = g, \mathcal{L} = P] \tag{1}$$

ATT((2004,0),t) represents the average group time treatment effect of ozone standards in time period t, among sectors that are only regulated in 2004 for ozone and sit in a county that is only regulated for ozone. Similarly, ATT((0,2005),t) represents the average group time treatment effect for $PM_{2.5}$. ATT((2004,2005),t) represents the average group time treatment effect of regulation for both ozone and $PM_{2.5}$ standards for this group.[17]

[17]If we want to distinguish the effect of ozone from the effect of $PM_{2.5}$ on the sectors treated for both, the group-time average treatment effect for $PM_{2.5}$ is the following:

$$ATT(g, t) = \mathrm{E}[Y_t(2004, 2005)|C = g, \mathcal{L} = P] - \mathrm{E}[Y_t(2004, 0)|C = g, \mathcal{L} = P]$$

which requires additional identifying assumptions, as discussed in Appendix B.II. Unfortunately, I cannot identify the effect of ozone on this group separately. See De Chaisemartin and D'haultfœuille (2023) for further results for cases with several treatments.

4.2 Identifying Assumptions

Let $D^p_{i,t}$ be the treatment indicator for sector i at time t for pollutant p, where $D^p_{i,t} = 1$ if sector i is treated at time t and $D^p_{i,t} = 0$ otherwise. The first identifying assumption is that treatment is irreversible:

Assumption 1: (Irreversibility of treatment) $D^p_{i,t}$ =0 for $t = \{2001, 2002, 2003\}$, $\forall i = 1, ..., n$ and for $p = \{Ozone,\ PM_{2.5}\}$ and for $t \geq 2004$

$$D^p_{i,t-1} = 1 \quad \text{implies that} \quad D^p_{i,t} = 1$$

Assumption 1 states that no one is treated before $t = 2004$ and that once a sector i begins to be treated for a specific pollutant, it continues to be treated in all subsequent periods.[18]

The second identifying assumption is limited treatment anticipation, meaning that unit treatment effects are zero for some period before treatment occurs. The announcement of new standards in 1997 was followed by lawsuits that created doubt that the regulation would be implemented.[19] After the Supreme Court upheld the regulation, the EPA first asked counties to report monitoring data and self-certify their regulatory status in 2003. The EPA used these data to designate counties for ozone in 2004 and for $PM_{2.5}$ in 2005.[20] Therefore, I assume that the potential anticipation period is one year for counties regulated for ozone and two years for those regulated for $PM_{2.5}$.

Assumption 2: (Limited Treatment Anticipation) There is a known $\delta \geq 0$ such that

$$\mathrm{E}[Y_t(g)|C = g, \mathcal{L} = P] = \mathrm{E}[Y_t(0)|C = g, \mathcal{L} = P] \quad \text{for all g such that} \quad t < g - \delta$$

where δ=1 for ozone and δ=2 for $PM_{2.5}$. Assumption 2 restricts anticipation of the treatment to be, at most, one year for the sectors treated for ozone and two years for the sectors treated for $PM_{2.5}$.

The third assumption is a version of parallel trends for triple-difference based on "never-treated" sectors:

Assumption 3: (Parallel Trends for Triple-difference Based on "Never-treated" Groups) Let δ be defined as in Assumption 2. For all g and $t \geq g - \delta$,

$$\begin{gathered}\mathrm{E}[Y_t(0,0) - Y_{t-1}(0,0)|C = g, \mathcal{L} = P] - \mathrm{E}[Y_t(0,0) - Y_{t-1}(0,0)|C = g, \mathcal{L} = NP] \\ = \\ \mathrm{E}[Y_t(0,0) - Y_{t-1}(0,0)|C = 0, \mathcal{L} = P] - \mathrm{E}[Y_t(0,0) - Y_{t-1}(0,0)|C = 0, \mathcal{L} = NP]\end{gathered}$$

[18] Even though a county's regulatory status switches from nonattainment to attainment after it complies with the standards, the treated plants still have the lowest achievable emission technologies specified in SIPs, and a Limited Maintenance Plan can be implemented to continue compliance.

[19] See "The US Court of Appeals for the D.C. Circuit Decision on EPA's Public Health Air Standards for Smog and Soot"

[20] The EPA used the annual fourth-highest daily maximum 8-hour concentration for ozone averaged over 2001-2003, while they considered the annual mean for $PM_{2.5}$ over 2001-2003.

In words, the difference in the evolution of average untreated outcomes among sectors with $\mathcal{L} = P$ and $\mathcal{L} = NP$ in the treated counties is the same as the difference of the evolution of average untreated outcome among sectors with $\mathcal{L} = P$ and $\mathcal{L} = NP$ in the untreated counties in the absence of treatment. Finally, the ATT(g,t) estimands using the never-treated group as a comparison group can be rewritten as follows:

$$
\begin{aligned}
ATT(g,t) = & \Bigg[\bigg(\mathrm{E}[Y_t|C = g, \mathcal{L} = P] - \mathrm{E}[Y_{g-1}|C = g, \mathcal{L} = P]\bigg) \\
& - \bigg(\mathrm{E}[Y_t|C = g, \mathcal{L} = NP] - \mathrm{E}[Y_{g-1}|C = g, \mathcal{L} = NP]\bigg)\Bigg] \\
& - \Bigg[\bigg(\mathrm{E}[Y_t|C = 0, \mathcal{L} = P] - \mathrm{E}[Y_{g-1}|C = 0, \mathcal{L} = P]\bigg) \\
& - \bigg(\mathrm{E}[Y_t|C = 0, \mathcal{L} = NP] - \mathrm{E}[Y_{g-1}|C = 0, \mathcal{L} = NP]\bigg)\Bigg]
\end{aligned} \tag{2}
$$

4.3 Implementation

To identify the group-time average treatment effects, I split sectors into those with $\mathcal{L} = P$ and those with $\mathcal{L} = NP$ for a specific pollutant. Among those with $\mathcal{L} = P$, I first estimate the "pseudo-ATT(g,t)'s", using treatment status. Then, I repeat the same step for $\mathcal{L} = NP$. Finally, I take the difference of these two differences. More specifically, I subtract the "pseudo- ATT(g,t)'s" for the units with $\mathcal{L} = NP$ from those with $\mathcal{L} = P$. The final difference is the triple-difference estimator for the ATT(g,t).[21] For inference, I bootstrap the standard errors and cluster at the county level to allow for potential correlation across sectors within the same county. Observations are weighted by the total employment for each county-sector pair in 2001.

Finally, I aggregate the group-time average treatment effects to calculate the interested effect of regulations:

$$
\theta = \sum_{g \in \mathcal{G}} \sum_{t} \omega(g,t) x ATT(g,t) \tag{3}
$$

where θ is the ATT, calculated as a weighted average of ATT(g,t) estimated in Equation 2.

4.4 Summary Statistics

The estimation sample is constructed using local labor market data from the Quarterly Workforce Indicators (QWI), sector pollution status from the Air Facilities System (AFS) Data, and county nonattainment status from the EPA's Green Book and AirNow files. These datasets were merged using FIPS county codes and three-digit NAICS sector codes. The sample is restricted to county-sector pairs with annual data on college and high-school employment for the entire study period.[22]

[21] The partition-specific DiDs do not have a causal interpretation under these assumptions.

[22] County-sector pairs with fewer than eleven years of observations were excluded. The QWI data suppressed observations that did not meet US Census Bureau publication standards for information disclosure. The average annual employment for the excluded observations was 19 workers, calculated from the available years. These sectors likely had fewer workers in the missing years, and small sectors are less likely to be significantly impacted by regulation.

This results in a balanced panel of 17,785 county-sector pairs in 2001, which are tracked over the next ten years. The sample includes 524 counties covering 17% of the U.S. population in 2000.[23] Table 8 in Appendix B.I compares the sectoral composition of employment in the estimation sample with that of the U.S. in 2001, showing that the sample closely mirrors the sectoral employment shares of the broader economy.[24]

Table 1 presents summary statistics for polluting and nonpolluting sectors of attainment counties and counties that switched to nonattainment status with the 1997 CAA Expansion; summary statistics are reported before the regulation in 2001. Panel A reports statistics for all workers, while Panels B and C divide the sample into college graduates and high school graduates and below.[25] Panels B and C summarize statistics for workers aged 25 and older because The QWI does not report the education levels of workers who are 24 or younger.

Panel A shows substantial differences between polluting and nonpolluting sectors within each group of counties. First, the polluting sectors are larger than the nonpolluting sectors. Second, workers in polluting sectors tend to earn higher wages than their counterparts in nonpolluting sectors; the college graduates in polluting sectors earn 26% more than those in nonpolluting sectors, while the difference is 28% for high school and below. Third, nonpolluting sectors have lower hiring and separation rates than polluting sectors. These observed differences suggest that it may also be important for the research design to control for unobserved differences across sectors.

Further, workers in nonattainment counties, which tend to be more urban and economically larger, earn relatively higher wages than those in attainment counties, more than 10% on average. This makes it important for the research design to address heterogeneity across counties, especially since the Great Recession occurred shortly after the designation of nonattainment counties. Differential impacts of the recession on switch counties and attainment counties could bias between-county comparisons of the effects of regulation on polluting sectors. This underscores why it is important that the estimation accounts for unobservable characteristics of sectors and counties.

4.5 Results

Table 2 presents the average treatment effect of regulations on employment in treated sectors of regulated counties. The coefficients are constructed by aggregating the estimated average group-time treatment effects using Equation 3. Panel A reports results for individuals with a college education

[23] The sample excludes counties without outdoor monitors and those regulated for previous standards. Nonattainment counties regulated before the 1997 Expansion have a higher population on average, as shown in Table 9, and those counties cover 69% percent of the U.S. population.

[24] Additionally, the table provides a comparison of the educational composition within sectors, indicating the shares of workers with college degrees and above, as well as those with high school degrees and below, in both the sample and the U.S. as a whole.

[25] See Table 9 for extended summary statistics for attainment counties, nonattainment counties that were regulated before the 1997 CAA Expansion, and counties that switched to nonattainment status with the 1997 Expansion in 2001. The counties that switched off the treatment before 1994 are included in the switched counties. The table also reports summary statistics for some college graduates.

Table 1: Summary Statistics Before the Regulation (2001)

	Attainment		Switch into Nonattainment	
	Nonpolluting	Polluting	Nonpolluting	Polluting
Panel A: Full Sample				
Employment (Median county-by-sector)	334	544	352	684
Average Monthly Earnings ($)	2,233	2,776	2,367	3,093
Hiring Rate	0.16	0.11	0.15	0.09
Separation Rate	0.16	0.12	0.16	0.10
Total Employment	8,685,444	3,725,048	3,728,670	2,430,348
Panel B: College and Above				
Average Monthly Earnings ($)	3,222	3,968	3,508	4,450
Hiring Rate	0.13	0.09	0.13	0.07
Separation Rate	0.14	0.11	0.13	0.09
Total Employment	1,733,883	912,294	769,989	653,781
Panel C: High School and Below				
Average Monthly Earnings ($)	1,971	2,446	2,059	2,693
Hiring Rate	0.14	0.10	0.13	0.08
Separation Rate	0.14	0.11	0.14	0.10
Total Employment	2,998,279	1,315,952	1,280,818	853,039
# of County x Sector	9,729	2,589	4,238	1,229

Note: This table reports the summary statistics for polluting and nonpolluting sectors in switched and attainment counties. Panel A reports summary statistics for all workers. Panels B and C divide the sample into college graduates and high school and below graduates over 24 years old.

or higher, while Panel B presents results for those with a high school education or lower.[26] Column (1) shows the average treatment effect of regulation on employment, aggregating the average group-time treatment effects of ozone alone, $PM_{2.5}$ alone, and both regulations together. Columns (2) and (3) separately report the average treatment effects for ozone and $PM_{2.5}$, respectively, while Column (4) shows the average treatment effect of both regulations on employment.

Column (1) indicates that the 1997 Expansion led to a 3.6% reduction in college employment in regulated sectors, with a 1.8% decrease in sectors regulated only for ozone (Column (2)) and a 2.6% drop in sectors regulated for PM2.5 (Column (3)). However, these findings are statistically insignificant. Interestingly, employment among college graduates in sectors regulated for both pollutants declines by nearly 9%. In contrast, employment among individuals with a high school degree or less decreases by 7.6% in regulated sectors. Specifically, noncollege employment fell by 6.7% in sectors regulated only for ozone and by 10% in those regulated only for PM2.5. Notably, the average treatment effect of both regulations indicates a 7% drop in employment for this group. These results suggest that environmental regulations have a more pronounced negative impact on employment for less-educated workers in regulated sectors. Moreover, there is significant variability in the impact of regulations, highlighting treatment heterogeneity.

[26] To align with the skill definition in the model, I only report two education categories. Appendix B.III provides the results for employment among workers with some college experience but no degree or associate degree.

Table 2: The Effect of Regulation on Employment

	Regulation	Ozone	$PM_{2.5}$	Both
	(1)	(2)	(3)	(4)
Panel A: College and Above				
	-0.036	-0.018	-0.026	-0.088***
	(0.023)	(0.040)	(0.024)	(0.022)
Panel B: High-School and Below				
	-0.076***	-0.067***	-0.100***	-0.069***
	(0.023)	(0.034)	(0.040)	(0.023)
Observations	195,635	164,582	144,023	140,899

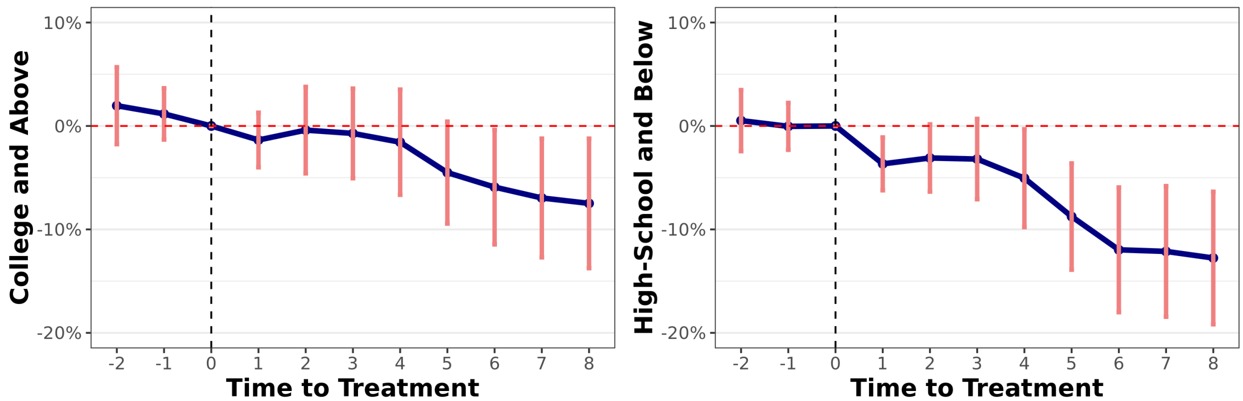
Note: This table reports the average treatment effect of regulations on the employment levels in treated sectors in regulated counties, which is constructed by aggregating the average group-time treatment effects using Equation 3. Panel A reports the employment results among individuals with a college education or higher, while Panel B presents results for those with a high school education or less. Bootstrapped standard errors (N=1000) are in parentheses and are clustered at the county level. The number of observations differs between columns because the treatment group varies with each group specification.

Dynamic Effects of Treatment: I plot the estimated average group-time treatment effect to understand how treatment effects vary with treatment duration. Figure 2 illustrates the dynamic effects of regulation on college and noncollege employment. It is natural to expect the effects to evolve over time because it often takes some time to develop and implement State Implementation Plans to reduce pollution (Curtis (2020)). Trends in employment in the regulated and unregulated sectors for the years prior to treatment are similar, as reflected by statistically insignificant pretend differences. For college graduates, employment begins to decline five years after treatment, reaching 7.4% after eight years. For noncollege graduates, employment in treated sectors starts declining around four years post-regulation, reaching a 13% reduction by year eight.

To explore treatment effect heterogeneity, Figure 3 plots the dynamic effects of ozone regulation alone, $PM_{2.5}$ regulation alone, and both regulations together for college and noncollege employment. By the end of the study period, the ozone regulation caused an approximate 6% (statistically insignificant) decline in employment for college graduates and a 12% decline for noncollege graduates. Moreover, college-educated workers in polluting sectors of counties regulated for $PM_{2.5}$ did not experience a significant decrease in employment. However, non-college-educated employment began to fall right after the $PM_{2.5}$ designation, eventually dropping 17% below 2003 employment levels. This suggests that non-college-educated workers were more adversely affected by $PM_{2.5}$ regulations than their college-educated counterparts.

Finally, for polluting sectors within counties regulated for both pollutants, college employment declined by 15% seven years after designation, while non-college employment dropped by 11% over the same period. This deviation from the prior trends, where non-college-educated workers typically experience more significant declines, highlights the variability in regulatory impact based on treatment heterogeneity and intensity. One potential explanation is that marginal abatement

Figure 2: Dynamic Effects of Regulation on Employment



Note: Figures above plot the average group-time treatment effect of regulation on college and noncollege employment, which is constructed by aggregating the average group-time treatment effects on event time. The red straight lines represent 95 percent confidence intervals from bootstrapped standard errors (N=1000). Standard errors are clustered at the county level.

costs may increase with the levels of pollution. Alternatively, variation in the elasticity of substitution between college and non-college employment across these groups could also play a role. These groups are categorized by treatment type, representing polluting sectors in regulated counties under distinct regulatory conditions.

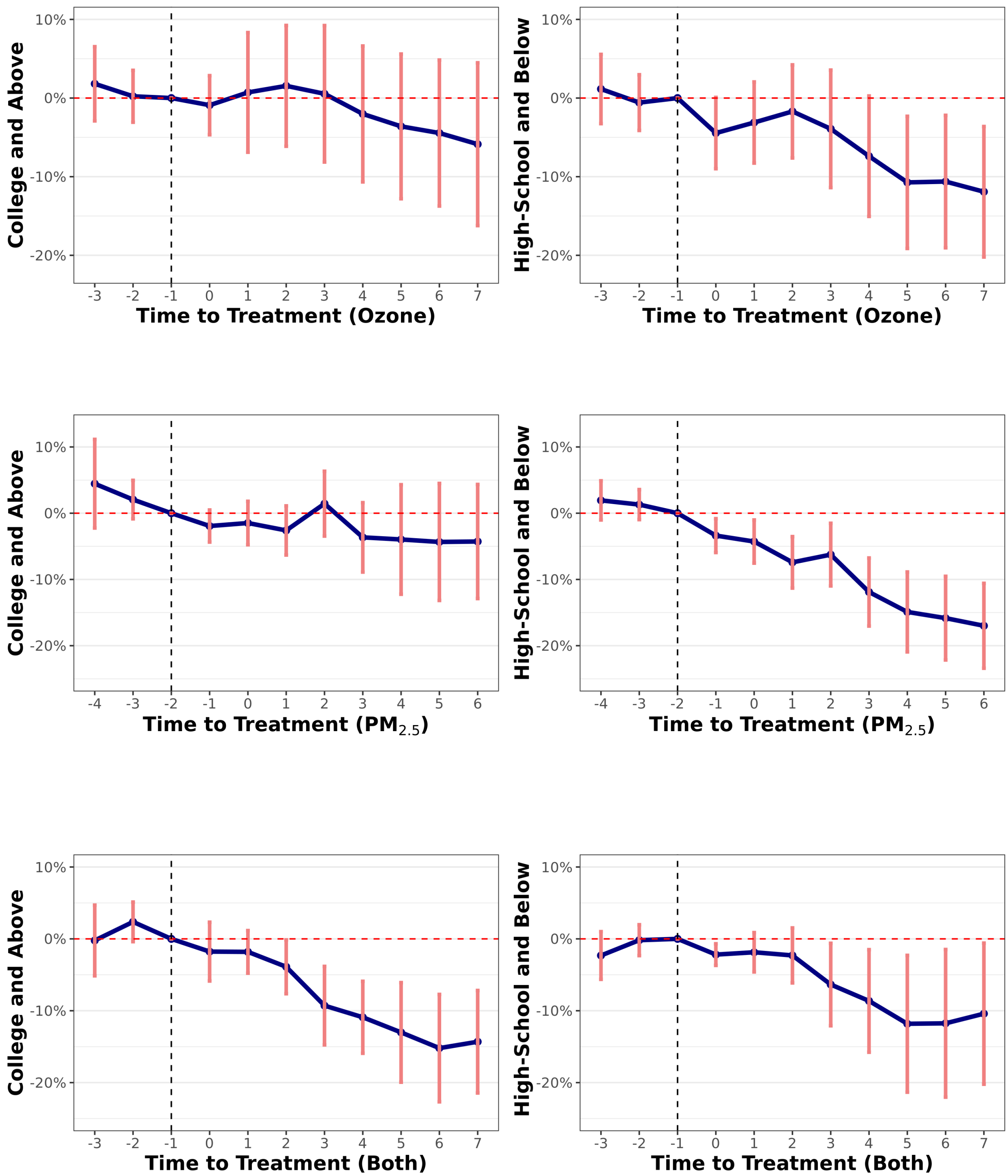
My findings are broadly consistent with the existing literature. Walker (2011) examines the employment effects of the 1990 CAA Amendments on regulated sectors, finding that employment in newly regulated, polluting sectors declined by more than 15 % over the decade following the regulatory change.[27] Curtis (2020) focuses exclusively on the effect of ozone regulation in 2004. His results indicate a statistically insignificant impact on employment.[28] However, his findings provide evidence of a decrease in the number of establishments in regulated counties, accompanied by an increase in establishment size.

My findings underscore the importance of heterogeneity in treatment effects across different groups over time. The disparities between college and non-college graduates highlight the need for careful evaluation of the distributional effects of regulations.

[27] As shown in Table 9, nonattainment counties regulated prior to the 1997 Expansion have higher population levels, and the polluting sectors in those counties are larger. Additionally, Walker estimates the impact of regulation on plant-level employment growth for different pollutants, such as ozone and PM_{10}, concluding that particulate matter has a more significant negative effect on plant-level employment growth.

[28] The sample in Curtis (2020) includes counties designated for ozone regulation for the first time in 2004, as well as attainment counties between 2000 and 2013. It covers six three-digit NAICS industries: Primary Metal Manufacturing, Paper Manufacturing, Nonmetallic Mineral Product Manufacturing, Chemical Manufacturing, Wood Product Manufacturing, and Petroleum and Coal Product Manufacturing.

Figure 3: Dynamic Effects of Regulation on Employment



Note: Figure 3 plots the average group-time treatment effect of ozone regulation, $PM_{2.5}$ regulation and both regulation on college and noncollege employment on event time. The red straight lines represent 95 percent confidence intervals from bootstrapped standard errors (N=1000). Standard errors are clustered at the county level.

5 Model

Place-based environmental regulations can improve local quality of life by reducing air pollution while simultaneously worsening local labor market conditions. As shown in Section 4, these regulations reduce employment in regulated sectors and may lower the earnings of workers undergoing job transitions (Walker (2013)). Workers may respond to these changes by relocating across local labor markets and/or shifting between sectors. I develop a general equilibrium framework that captures these dynamics, characterizing how environmental regulation impacts household welfare through shifts in pollution exposure, wages, and employment. This framework integrates workers' residential location choices with labor market frictions and pollution exposure. To model unemployment, I incorporate search frictions into a two-sector model of clean and dirty production within local labor markets.

5.1 Environment

Time is discrete, infinite, and indexed by t ≥ 0. For simplicity, time subscripts are omitted unless needed for clarity. There are R local labor markets, indexed by $r \in \{1, 2, ..., R\}$. Each location r is characterized by its exogenous productivity A_r and residential amenities ψ_r. Each location has a positive mass of risk-neutral, infinitely lived workers and profit-maximizing firms. Both workers and firms discount the future at a common discount factor $\beta \in (0, 1)$.

There are two sectors in each location, indexed by $j \in \{c, d\}$ where c represents the clean sector and d the dirty sector. The sectors differ in terms of pollution emission per unit of output, e_j. The government regulates air pollution by imposing performance standards, which limit the emission per unit of output to $\bar{e}$ for dirty sectors in locations with high pollution levels.

Firms post vacancies, which can be filled through a matching process or remain vacant. Firms produce sector-specific goods using only labor as an input. The output of each worker-firm match depends on location-specific productivity and match-specific productivity. Additionally, there is a constant return to scale technology that uses the goods produced by each sector as inputs to produce the numeraire consumption good.

A worker can be employed or unemployed.[29] Workers differ *ex-ante* based on their level of education, which is indexed by $i \in \{l, h\}$. Here, l represents individuals with a high-school diploma or lower, while h represents those with a college degree or higher. More highly educated workers are assumed to be more productive. Regardless of employment status, each worker incurs the local cost of housing and enjoys local amenities. Wages vary with location, sector, and level of education, and unemployed workers receive unemployment benefits. Unemployed workers choose where to live and search for jobs and are assumed to move freely across locations. Employed workers do not search for jobs; in other words, there is no on-the-job search and job-to-job transitions.

[29] To simplify the model, I abstract from labor force participation decisions.

For each local labor market, λ_r denotes the labor force size, defined as:

$$\lambda_r = \sum_{j\in\{c,d\}} \sum_{i\in\{l,h\}} n^i_{r,j} + \sum_{i\in\{l,h\}} u^i_r \quad r \in \{1,....,R\} \tag{4}$$

Here, $n^i_{r,j}$ is the measure of employed workers of type i in sector j in location r, and u^i_r is the measure of unemployed workers.

5.2 Matching Process

Unemployed workers search over all sectors and locations. Worker types are observable, leading to segmented labor markets, meaning that high-educated and low-educated workers do not compete for the same jobs. The number of matches in sector j within location r for workers of type i is determined by the following matching function:

$$M^i_{r,j} = M(u^i_r, v^i_{r,j}) = \mu^i_j (u^i_r)^{\gamma} (v^i_{r,j})^{1-\gamma} \tag{5}$$

Here, μ^i_j represents the matching efficiency, γ is the matching elasticity parameter, and $v^i_{r,j}$ denotes the number of posted vacancies.[30]

The probability of filling a vacant job is calculated as the ratio of the number of matches produced by the matching function to the number of posted vacancies. This probability is expressed as a function of $\theta^i_{r,j} = \frac{v^i_{r,j}}{u^i_r}$: [31]

$$q(\theta^i_{r,j}) = \mu^i_j (\theta^i_{r,j})^{-\gamma} \tag{6}$$

The probability of finding a job for type i in sector j within location r is the ratio of the number of matches to the number of unemployed workers of type i searching in location r. This probability is represented by $\phi^i_{r,j}$:

$$\phi^i_{r,j} = \mu^i_j (\theta^i_{r,j})^{1-\gamma} = q^i_j(\theta^i_{r,j})\theta^i_{r,j} \tag{7}$$

5.3 Firms

Firms in each sector post vacancies for both worker types, and if they match with a worker, they produce a sector-specific good using only a labor input:[32]

$$y^i_{r,j} = A_r z^i_j \tag{8}$$

[30] In contrast to a one-sector model, a Cobb-Douglas matching technology with two sectors can be interpreted in multiple ways. For instance, Hafstead and Williams III (2018) use a Cobb-Douglas, constant returns aggregate matching function, $m_j = \mu_j (u_j)^{\gamma} v_j (v_j + v_{-j})^{-\gamma_j}$, which simplifies to the standard Cobb-Douglas form when only one sector is present. I consider both approaches, and my choice is made for simplicity following Phelan and Trejos (2000). The following constraint must be satisfied: $M^i_{r,c} + M^i_{r,d} \leq u^i_r$.

[31] The ratio of vacancies to unemployed workers is also known as the labor market tightness, in this case, θ represents sectoral tightness given the structure of the matching function.

[32] I consider single worker-firm matches following the literature (Pissarides (2000), Kuhn et al. (2021), Fernández Intriago (2019)).

The period output, $y^i_{r,j}$, is the product of the location-specific productivity, A_r, and the match-specific productivity, z^i_j.

The value of a matched firm $J^i_{r,j}(\lambda)$ is given by:

$$J^i_{r,j}(\lambda) = \underbrace{p_j A_r z^i_j - w^i_{r,j}}_{\text{Current profit}} + \underbrace{\beta\Big\{\pi^i_{r,j}\mathbf{E}_{\lambda'}[V^i_{r,j}(\lambda')] + (1-\pi^i_{r,j})\mathbf{E}_{\lambda'}[J^i_{r,j}(\lambda')]\Big\}}_{\text{Expected value next period}} \tag{9}$$

where $\lambda = \{n^l_{r,j},\ u^l_r,\ n^h_{r,j},\ u^h_r\ \forall r,\ \forall j\}$ represents the state of the economy. The equation can be divided into two parts: the first part is the firm's current profit, where p_j denotes the price of the good and $w^i_{r,j}$ denotes the wage paid to the worker. The second term is the expected value in the next period. The worker-firm match will be dissolved with the exogenous probability of $\pi^i_{r,j}$, in which case the firm will get the value with a vacancy, $V^i_{r,j}$, or with probability $1-\pi^i_{r,j}$, the match will continue, in which case the firm will get the value of a matched firm, $J^i_{r,j}$.

The value of a firm with a vacancy $V^i_{r,j}(\lambda)$ is given by:

$$V^i_{r,j}(\lambda) = -\kappa^i_j + \beta\Big\{q(\theta^i_{r,j})\mathbf{E}_{\lambda'}[J^i_{r,j}(\lambda')] + (1-q(\theta^i_{r,j}))\mathbf{E}_{\lambda'}[V^i_{r,j}(\lambda')]\Big\} \tag{10}$$

where κ^i_j denotes the cost of vacancy. With the job filling probability $q(\theta^i_{r,j})$, the firm matches with a worker of type i, starts production next period, and gets the value of a matched firm. With complementarity probability $1-q(\theta^i_{r,j})$, the firm continues searching and gets the value of a firm with a vacancy.

Imposing free-entry in equilibrium, i.e., $V^i_{r,j} = 0$, yields the following job creation condition:

$$\kappa^i_j = \beta q(\theta^i_{r,j})\mathbf{E}_{\lambda'}[J^i_{r,j}(\lambda')] \tag{11}$$

This condition means that the cost of vacancy equals the expected value of filling the vacancy in the equilibrium.

Emission standards:

Only the dirty sector produces emissions, which are assumed to be proportional to output. Performance standards restrict the emissions of pollutant p per unit of output, which is specified as follows: [33]

$$\frac{e^p_r}{y_{r,d}} = (1-\Gamma^p_{r,d})\nu^p_{r,d} \tag{12}$$

where $\nu^p_{r,d}$ is a fixed emission rate and $\Gamma^p_{r,d}$ denotes the abatement rate. $Y_{r,d}$ represents total output, which is defined as:

$$Y_{r,d} = n^l_{r,d}y^l_{r,d} + n^h_{r,d}y^h_{r,d} \tag{13}$$

[33] The pollutants p include five key criteria air pollutants: ammonia (NH_3), nitrogen oxides (NO_x), fine particulate matter ($PM_{2.5}$), sulfur dioxide (SO_2), and volatile organic compounds (VOCs).

Thus, the emission per unit of output can be reduced by abatement effort. Emissions per unit of output must be less than or equal to the government-set threshold, $\bar{e}$: [34]

$$\frac{e^p_{r,d}}{y_{r,d}} \leq \bar{e}^p \tag{14}$$

The cost of abatement per unit of output is denoted by $\bar{\Delta}(\Gamma)$. After incurring the abatement cost, the net output for the dirty sector is

$$\bar{y}_{r,d} = (1 - \bar{\Delta}(\Gamma^p_{r,d}))y_{r,d} \tag{15}$$

When the dirty sector is regulated, the decrease in net output results in the decrease in value of a match for firms ($J_{r,d}$ in Equation (9)), leading to fewer vacancy postings by firms in the dirty sector. This reduction lowers the probability of finding a job ($\phi_{r,d}$ in Equation (7)) in dirty sectors within regulated locations. However, it may have ripple effects on clean sectors within the same location and on sectors in other locations. This channel is a key mechanism for how regulation affects local labor markets and worker welfare.

Consumption Good

The final consumption good is produced by aggregating the output of the clean and dirty sectors using a constant elasticity of substitution (CES) aggregation function, where the consumption good is assumed to be the numeraire:

$$Y = \left(\Omega Y_c^\chi + (1-\Omega)Y_d^\chi\right)^{1/\chi} \tag{16}$$

Here, Ω and $1-\Omega$ represent the share parameters for the clean and dirty sectors, respectively. The elasticity of substitution between Y_c and Y_d is given by $1/(1-\chi)$.

The input markets are assumed to be perfectly competitive, implying that the prices for the clean and dirty goods are as follows:

$$p_c = \Omega \left(\Omega Y_c^\chi + (1-\Omega)Y_d^\chi\right)^{\frac{1-\chi}{\chi}} Y_c^{\chi-1} \tag{17}$$

$$p_d = (1-\Omega) \left(\Omega Y_c^\chi + (1-\Omega)Y_d^\chi\right)^{\frac{1-\chi}{\chi}} Y_d^{\chi-1} \tag{18}$$

5.4 Workers

Workers receive utility from consuming the numeraire good, which is a composite of the clean and dirty goods, a unit of housing, and local amenities. Each worker is endowed with an education level and can either be employed or unemployed. Employed workers inelastically supply one unit of labor and earn wages depending on their education level, sector of work, and location. Unem-

[34]Firms treat this threshold as exogenous, as State Implementation Plans require existing polluting facilities to adopt the lowest achievable emission rate technologies, regardless of cost, to meet the National Ambient Air Quality Standards.

ployed workers receive unemployment benefits, denoted as b, which vary depending on their level of education. Additionally, they choose where to live and search for a job, implying distinct local labor markets. Unemployed workers are assumed to move across locations freely.

The value function of unemployed worker k of type i who lives in region r is characterized as:

$$\begin{aligned} U_r^{i,k}(\lambda) = & \underbrace{b^i - P_r^h + \psi_r + \epsilon_r^k}_{\text{Flow utility}} \\ & + \beta \Big\{ \underbrace{\phi_{r,c}^i \mathbb{E}_{\lambda',\epsilon'} \left[E_{r,c}^i(\lambda') + \epsilon_r'^k \right]}_{\text{Finding a job in clean sector}} + \underbrace{\phi_{r,d}^i \mathbb{E}_{\lambda',\epsilon'} \left[E_{r,d}^i(\lambda') + \epsilon_r'^k \right]}_{\text{Finding a job in dirty sector}} \\ & + \underbrace{(1 - \phi_{r,c}^i - \phi_{r,d}^i) \mathbb{E}_{\lambda',\epsilon'} \left[\tilde{U}^{i,k}(\lambda') \right]}_{\text{Staying unemployed and choosing a location}} \Big\} \end{aligned} \tag{19}$$

The value function of an unemployed worker can be separated into two parts. The first part denotes the flow utility in the current period, given the worker's location. She receives unemployment benefits, b^i, and pays the price of a unit of housing in location r, denoted as P_r^h. She enjoys the local amenities, ψ_r, and receives an idiosyncratic location-specific preference shock, ϵ_r^k, drawn from a Type I Extreme Value distribution. The second term is the expected value of the next period, which depends on three possible outcomes: with probability $\phi_{r,c}^i$ she finds a job in the clean sector and receives the value of an employed worker in that sector, $E_{r,c}^{i,k}$, with probability $\phi_{r,d}^i$ she finds a job in the dirty sector and receives the value of an employed worker in that sector, $E_{r,d}^{i,k}$, and with probability $(1 - \phi_{r,c}^i - \phi_{r,d}^i)$, she stays unemployed and can choose a location to live and search for a job, where $\tilde{U}^{i,k}(\lambda) = \max_p U_p^i(\lambda) + \epsilon_p'^k$ for $p \in \{1, ..., N\}$.

The value function of an employed worker k is:

$$E_{r,j}^{i,k}(\lambda) = \underbrace{w_{r,j}^i - P_r^h + \psi_r + \epsilon_r^k}_{\text{Current flow utility}} + \beta \Big\{ \underbrace{\pi_{r,j}^i \mathbb{E}_{\lambda',\epsilon'} \left[\tilde{U}^{i,k}(\lambda') \right]}_{\text{Separation}} + \underbrace{(1 - \pi_{r,j}^i) \mathbb{E}_{\lambda',\epsilon'} \left[E_{r,j}^i(\lambda') + \epsilon_r'^k \right]}_{\text{Continued employment}} \Big\} \tag{20}$$

During the current period, the worker receives a wage, pays the housing cost while enjoying local amenities, and gets location-specific preference shocks. Next period, with probability $\pi_{r,j}^i$, she loses her job and can choose a new location in which to live and search for a job; and with probability $1 - \pi_{r,j}^i$, she stays employed and gets the value of being employed in the same sector.

Location Choice

An unemployed worker will choose where to live and search for a job to maximize their value function:

$$\max_r U_r^i(\lambda) + \epsilon_r^k \tag{21}$$

Assuming the idiosyncratic location-preference shock, ϵ_r^k is drawn from a $Gumbel(-\rho\nu, \rho)$ distribution, we can write the probability of choosing region p as: [35]

$$\delta_p^i = \frac{exp(U_p^i(\lambda))}{\sum_{r=1}^N exp(U_r^i(\lambda))} = \frac{1}{1 + \sum_{r\neq p}^N exp(\frac{U_r^i(\lambda) - U_p^i(\lambda)}{\rho})} \tag{22}$$

Location-specific amenities

Location-specific amenities, denoted by ψ_r, depend on exogenous amenities, ψ_r^B, which capture fixed local characteristics and the endogenous damages from ambient air pollution, $D(a_r)$. This relationship is defined as follows:

$$\begin{aligned} \psi_r &= \psi_r^B \left[1 - D(a_r)\right] \\ \psi_r &= \psi_r^B \left[1 - \sum_{m=1}^R \sum_{p=1}^P MD_{mr}^p e_m^p\right] \end{aligned} \tag{23}$$

Here, local ambient pollution, a_r, is influenced by emissions from all locations, formulated as $a_r = A_r(\mathbf{e})$, where $\mathbf{e} = (e_m^p)$ for all locations $m \in 1, \ldots, R$ and pollutants p. Total damages, $D(a_r)$, reflect the emissions of pollutant p from dirty sectors in location m and the corresponding marginal damages on a worker in location r, represented by MD_{mr}^p.[36] This approach accounts for how emissions of ozone and particulate matter precursors from multiple locations contribute to ambient air pollution across regions.

Housing Supply

Following Saiz (2010), I assume the housing supply curve is upward-sloping with location-specific elasticities and intercepts. The housing supply curve is parametrized as follows:

$$P_r^h = \bar{H}_r \lambda_r^{\sigma_r} \tag{24}$$

$\bar{H}_r$ denotes the location-specific intercepts, which embed variations in local construction costs. λ_r represents the population in location r, and while location-specific elasticities, σ_r, reflect differences in the amount of land available for production and the strictness of local land-use restrictions, such as zoning laws.

[35]See Appendix C.I for derivation of the value of unemployed and employed workers as a function of the location choice probabilities.

[36]Local ambient pollution, primarily measured by fine particulate matter ($PM_{2.5}$) and five other key criteria pollutants, serves as a precursor to ambient pollution. This approach aligns closely with existing literature Muller and Mendelsohn (2007), Hollingsworth et al. (2024), US Environmental Protection Agency (1999). Most pollution-related welfare losses are attributed to mortality due to particulate matter exposure, with US Environmental Protection Agency (1999) estimating that mortality accounts for 90% of these welfare impacts, as detailed in Table 8-1.

5.5 Total Surplus and Wage Determination

To determine wages, I assume that a worker and firm split the joint surplus of the match according to Nash bargaining. By using the free-entry equilibrium condition, the joint match surplus of a job filled by a worker of type i in sector j and region r is [37]

$$S^i_{r,j}(\lambda) = J^i_{r,j}(\lambda) + E^i_{r,j}(\lambda) - U^i_r(\lambda) \tag{25}$$

Nash bargaining implies that the total match surplus is split according to the bargaining weights so that the firm's share of the surplus is $J^i_{r,j}(\lambda) = (1-\eta)S^i_{r,j}(\lambda)$ and the worker's share of the surplus is $E^i_{r,j}(\lambda) - U^i_r(\lambda) = \eta S^i_{r,j}$, where η is the worker's bargaining power with $\eta \in \{0, 1\}$.

By substituting for the value of filling a vacancy, $J^i_{r,j}$, and for the difference between the value of employment and unemployment, $E^i_{r,j}(\lambda) - U^i_r(\lambda)$, the total surplus $S^i_{r,j}$ can be rewritten as [38]

$$\begin{aligned} S^i_{r,j} &= p_j y^i_{r,j} - b^i + \beta(1-\pi^i_{r,j})S^i_{r,j} - \beta\eta\phi^i_{r,j}S^i_{r,j} - \beta\eta\phi^i_{r,-j}S^i_{r,-j} \\ &+ \beta(\pi^i_{r,j} - (1-\phi^i_{r,j} - \phi^i_{r,-j}))\rho log(1/\delta^i_r) \end{aligned} \tag{26}$$

Furthermore, the wage equation can be characterized using $J^i_{r,j} = (1-\eta)S^i_{r,j}$ and $E^i_{r,j} - U^i_r = \eta S^i_{r,j}$ and the equilibrium condition $J^i_{r,j} = \frac{\kappa^i_j}{\beta q(\theta^i_{r,j})}$. The wage equation for a worker of type i in sector j, region r can be expressed as:

$$\begin{aligned} w^i_{r,j} &= \eta p_j y^i_{r,j} + (1-\eta)b^i + \eta\theta^i_{r,c}\kappa^i_c + \eta\theta^i_{r,d}\kappa^i_d \\ &- \beta(1-\eta)(\pi^i_{r,j} - (1-\phi^i_{c,r} - \phi^i_{d,r}))\rho log(1/\delta^i_r) \end{aligned} \tag{27}$$

5.6 Steady State Equilibrium

Letting the final consumption good be the numeraire of this economy, given a set of constant exogenous parameters $\{\gamma, \mu^i_j, A_r, z^i_j, \kappa^i_j, \pi^i_{r,j}, \beta, b^i, \eta, \psi_r, \rho, v_{r,j}, \bar{H}_r, \sigma_r, \Omega, \chi, \Gamma_{r,j}\}_{r=\{1,....,N\},j=\{c,d\},i=\{l,h\}}$, a steady state equilibrium is the set of values $\{U^i_r, E^i_{r,j}, J^i_{r,j}\}_{r=\{1,....,N\},j=\{c,d\},i=\{l,h\}}$, the location choice probabilities,$\{\delta^i_r\}_{r=\{1,....,N\},i=\{l,h\}}$, wages $\{w^i_{r,j}\}_{r=\{1,..,N\},j=\{c,d\},i=\{l,h\}}$, prices $\{p_c, p_d, \{P^h_r\}_{r=\{1,...,N\}}\}$ and allocations $\{n^i_{r,j}, u^i_r\}_{r=\{1,....,N\},j=\{c,d\},i=\{l,h\}}$ such that:

1. The free entry condition, $V^i_{r,j} = 0$, holds for both sectors and both education levels in each location, which implies:
$$\frac{\kappa^i_j}{\beta q(\theta^i_{r,j})} = \frac{p_j A_r z^i_j - w^i_{r,j}}{1-\beta(1-\pi^i_{r,j})} \tag{28}$$
2. Unemployed workers decide where to live and search for a job to maximize utility so that move probabilities satisfy equation 22.

[37] For workers of type i, the outside option of not agreeing is unemployment, and for firms, the job posting remains vacant. Hence, the agreement requires that $E^i_{r,j}(\lambda) \geq U^i_r(\lambda)$ and $J^i_{r,j}(\lambda) \geq V^i_{r,j}(\lambda)$, which is zero in the equilibrium.

[38] See Appendix C.II for derivation.

3. Workers and firms split the surplus that maximizes the generalized Nash Product, yielding wages function in equation 27.

4. The intermediate goods market clears in aggregate for both sectors.

5. The housing market clears in each local market according to equation 24.

6. There is a stationary labor distribution of workers over employment status and across regions. (i.e. Inflows = Outflows) [39]

6 Calibration

I calibrate the model parameters to reflect key characteristics of 21 commuting zones in North Carolina prior to the implementation of the 1997 regulatory standards. A commuting zone is considered regulated if at least one county within it is subject to regulation. I focus on the manufacturing sector as the designated "dirty" sector because it holds 75% of pollutant permits issued in the state.[40]

The parameter calibration proceeds in two steps. First, I estimate or calibrate a subset of parameters that can be directly derived from the data or sourced from existing literature. In the second step, I calibrate the vector of remaining parameters, Θ:[41]

$$\Theta = \{\underbrace{z^i_{r,j}, \kappa^i_j, \pi^i_{r,j}}_{\text{Labor Market}}, \quad \underbrace{\psi_r}_{\text{Local Amenities}}, \quad \underbrace{\Gamma^p}_{\text{Abatement Rate}} \quad \} \quad \text{where} \quad \forall r \in \{1, \dots, 21\},\ i \in \{l, h\},\ j \in \{c, d\}$$

6.1 Externally Calibrated Parameters

I set the discount factor, β, to 0.96, reflecting an average annualized interest rate of 4 percent. Following Kuhn et al. (2021), I set the matching elasticity, γ, to 0.4711, and the matching efficiency, μ, to 0.4371. For the worker bargaining parameter, I follow the standard approach in the literature by setting $\eta = \gamma$.[42]

Emission Related Parameters

Emission intensity, $\nu^p_{r,d}$, represents the emissions of pollutant p per unit of dirty sector output in commuting zone r. I gathered emissions data from the manufacturing sector in each county using

[39] Please see Appendix C.III for further details.

[40] In North Carolina, counties are classified as regulated under ozone or $PM_{2.5}$ standards or attainment status. Figure 12 shows the number of nonattainment counties over the years in North Carolina, while Figure 4 displays the 2000 commuting zones according to their regulatory status. On average, regulated counties account for 50% of manufacturing employment in their commuting zones as shown in Table 11. The utility sector is excluded due to its additional regulatory requirements, such as North Carolina's Clean Air Interstate Rule (CAIR), aligning with existing literature Hollingsworth et al. (2024).

[41] Notably, I adjust the notation here slightly from the model section, as I do not separate location-specific productivity, A_r, and sector-worker type match productivity, z^i_j in the calibration process. Instead, the pinned-down productivity parameters represent the productivity of each sector-worker type in commuting zone r.

[42] This is commonly referred to as the Hosios condition in the literature.

the 2001 NEI files and used payroll data from the Bureau of Economic Analysis at the county-sector level as a proxy for manufacturing economic activity. Both emissions and payroll data were aggregated to the commuting zone level. Emission intensity for each pollutant was calculated by dividing total emissions by total payroll in each commuting zone, providing a measure of pollution relative to economic activity.

Table 3: Externally calibrated parameters

Description	**Parameter**	**Value**	**Source**
Discount factor	β	0.96	*Annual Interest Rate 4%*
Matching elasticity	γ	0.4711	Kuhn et al. (2021)
Worker bargaining power	η	0.4711	Kuhn et al. (2021)
Matching efficiency	μ	0.4371	Kuhn et al. (2021)
Emission			
Emission intensity	$\nu^p_{r,d}$		*Author's calculation*
Marginal damages	MD^p_{mr}		*Author's calculation (AP3 Model)*
Abatement cost level	α_1	1	Normalized
Abatement cost curvature	α_2	2.8	Nordhaus (2008),
Housing Market			
Housing elasticity	σ_r		Saiz (2010)
Housing constant	$\bar{H}_r$		*Author's calculation*
CZ with Median Unemployment Rate Parameters			
Productivity (Clean - Low skill)	$\bar{z}^l_c$	1	*Normalized*
Job separation rates			
Clean Sector - Low skill	π^l_c	0.054	*Author's calculation*
Dirty Sector - Low skill	π^l_d	0.12	*Author's calculation*
Clean sector - High skill	π^h_c	0.019	*Author's calculation*
Dirty sector - High skill	π^h_d	0.052	*Author's calculation*
Final good substitution	χ	0.75	Hafstead and Williams III (2018)
Vacancy posting costs curvature	c	0.4	Schulz (2024)

Note: The table presents the model parameters that are set externally. Emission intensity parameters are calculated using emissions data from the manufacturing sector in each county from the 2001 NEI files and payroll data from the Bureau of Economic Analysis at the county-sector level as a proxy for manufacturing economic activity. Both emissions and payroll data were aggregated to the commuting zone level. Marginal damages per capita are constructed using the Air Pollution Emission Experiments and Policy Version 3 (AP3) model. Finally, I construct sector-worker type specific job separation rates using monthly data from the Current Population Survey that averaged over the 5-year period from 1998 to 2003.

To estimate per capita marginal damages from manufacturing sector emissions, $MD^p_{m,r}$, I use the Air Pollution Emission Experiments and Policy Version 3 (AP3) model. This integrated assessment model of atmospheric transport links emissions from five key criteria air pollutants to $PM_{2.5}$ exposures, physical impacts, and associated monetary damages across the contiguous United States at the county level (Muller and Mendelsohn, 2007, 2009; Muller et al., 2011). Using emissions data from the manufacturing sector in 2001, I construct a county-level marginal damage per capita matrix, which is then aggregated to the commuting zone level. I assume that marginal damages are constant over time.[43]

The cost of abatement per unit of output, $\bar{\Delta}(\Gamma)$, is specified as $\alpha_1\Gamma^{\alpha_2}$ following Nordhaus (2008). The curvature parameter α_2 is set to 2.8, while α_1 is set to 1, following Nordhaus (2008) and Hafstead and Williams III (2018).

Housing Market Parameters I use the ACS 2000 5% sample to construct the rental price index across commuting zones in my sample. The housing elasticities are taken from Saiz (2010), and location-specific constants are calibrated to match the predicted rental index value using housing elasticities and the labor force distribution in commuting zones.[44]

Parameters in the CZ with the median unemployment

In equilibrium, the labor force distribution remains stationary across locations, sectors, and employment statuses.[45] Furthermore, the vacancy posting problem that firms face in each commuting zone is characterized by Equations (32) and (33), which depend solely on local labor market parameters, independent of amenity fixed effects, location-specific idiosyncratic shocks, and housing factors. This framework enables the calibration process to be divided into two components: "within location" and "across location".[46] I first focus on "within location" component to pin down local labor market parameters. Once these are determined, location-specific amenity fixed effects are calibrated to satisfy the equilibrium conditions "across locations", using Equation (19) and (22).

Another implication of the stationary labor force distribution is that "within location" components can be solved independently for each location. To calibrate the common local labor market parameters across locations, I focus on the commuting zone with the median unemployment rate, following an approach similar to Kuhn et al. (2021). Using the CPS data and the approach discussed in Section 3, I construct worker flows—including separation and job-finding rates by sector and worker type—specifically for this commuting zone. Separation rates are taken directly from the data.

6.2 Calibration of Structural Parameters

Three subsets of model parameters are calibrated internally. They are given by the Θ vector. First, focusing on the commuting zone with the median unemployment rate, I pin down the vacancy posting costs, κ_j^i, and the productivity of sector-worker type matches, z_j^i, in that location, with the

[43] The AP3 model combines data on emissions from various sources and population density to estimate damages from ambient air pollution. My analysis focuses on emissions from manufacturing sectors in 2001 at the area-source level. The model considers infant mortality and mortality rates for individuals over 30 years old to calculate damages. I use the 2001 county-level population of individuals over 30 to estimate damages, as the model emphasizes working households.

[44] See Appendix D.I for details about rental index construction and housing market parameters.

[45] Although there is labor mobility across spaces and sectors and flows between employment statuses, equilibrium requires that worker inflows and outflows are balanced. For further details on worker flows, see Appendix C.III.

[46] The surplus functions are derived from the difference between the value functions for employed (Equation 20) and unemployed (Equation 19) workers. Intuitively, the difference in the current flow utility between being employed and unemployed arises solely from the difference in wages and unemployment benefits; regardless of employment status, workers pay rent and enjoy amenities. See Appendix C.II for further details on the derivation of surplus functions.

productivity of clean sector–low-skill worker matches, $\bar{z}_c^l$, normalized to 1.

The cost of posting a vacancy, denoted by $v_{r,j}^i$, is specified as a convex function given by $\frac{\kappa_j^i}{1+c}(v_{r,j}^i)^{(1+c)}$, with the curvature parameter c set to 0.4, following Schulz (2024). This convex function implies that the cost of posting vacancies rises more than proportionally as the number of vacancies increases, discouraging firms from posting excessively high numbers of vacancies. The base cost of posting a vacancy, κ_j^i, is assumed to be constant across commuting zones. To calibrate the vacancy posting costs and productivity parameters, I target sector-specific job-finding rates for each worker type, constructed from CPS data, along with relative average hourly wages.

Using the calibrated values of κ_j^i and the clean sector–low-skill wage in the median unemployment commuting zone as a benchmark, I calibrate the second subset of parameters, which includes sector-worker type-specific productivities, $z_{r,j}^i$ and separation rates, $\pi_{r,j}^i$, across other commuting zones. This step targets differences in average hourly wages relative to the baseline wage and the shares of clean sector employment and unemployment rates for each skill type.

The targeted moments were derived using data from the 5 percent sample of the 2000 U.S. Census, the CPS, and the QWI datasets. To estimate the labor force distribution by education level across commuting zones and employment status, I follow the approach of Dorn (2009).[47] After identifying the number of employed and unemployed workers by education level in each commuting zone, I calculate the employment shares in the clean and dirty sectors by education level based on the observed shares in the QWI dataset.[48] The QWI dataset provides average monthly earnings by sector and education level. To adjust for differences in hours worked, I calculate average hourly wages by dividing these monthly earnings by monthly working hours derived from CPS data.[49]

The final subset of parameters to calibrate are location-specific base-level amenities. Using the calibrated labor market parameters and rent parameters, along with Equation (19), I construct the unemployed workers' value function, excluding the location-specific amenity fixed effect, for each commuting zone as $\hat{U}_r^i = U_r^i - \psi_r^i$. I then target the observed share of unemployed workers by skill type across commuting zones to recover the amenity fixed effects, ψ_r^i. Specifically, I employ an approach analogous to conditional choice probability methods for discrete choice models, applying Equation (22) as follows:

$$\log\left(\frac{\delta_r^i}{\bar{\delta}^i}\right) = \left(\hat{U}_r^i + \psi_r^i - (\bar{\hat{U}}^i + \bar{\psi}^i)\right) \tag{29}$$

Here, δ_r^i denotes the observed share of unemployed workers of type $i \in \{l, h\}$ in commuting zone r, while $\bar{\delta}^i$ denotes the observed share in the commuting zone with the median unemployment rate. I normalize the amenity fixed effects, $\bar{\psi}^i$, in this median commuting zone to 1 and derive base-level amenities from Equation (23). The emission of pollutant p in each commuting zone is calculated by multiplying dirty sector production by the emission intensity of pollutant p, i.e., $e_r^p = \nu_{r,d}^p \cdot y_{r,d}$.

[47] For further details, please see Appendix A.III.

[48] The fit of this method is assessed by comparing computed unemployment rates for commuting zones with those calculated using Local Area Statistics data, as shown in Figure 13.

[49] The CPS reports usual weekly hours worked; to calculate monthly hours, I multiply the usual weekly hours by 4.3.

The damages from air pollution are then derived using the marginal damages per capita from the AP3 model and the calculated emissions of pollutant p.

6.3 Parameters Estimates and Model Fit

Table 4 reports the calibrated parameters. Table 5 presents the targeted and untargeted data moments and their model counterparts in the commuting zone with the median unemployment rate. While all parameters are determined jointly in the first step, the mapping between data moments and model parameters is quite intuitive. The base costs of vacancy posting, κ_j^i, are informed by the job-finding rates for each skill type in clean and dirty sectors. Higher vacancy posting costs decrease job-finding rates by decreasing vacancy postings. Moreover, relative average hourly wages primarily determine the match-specific productivity by sector and worker type, z_j^i, relative to the productivity of low-skill workers in the clean sector, $\bar{z}_c^l$.

The difference in vacancy posting costs shown in Table 4 suggests that firms in the dirty sector face higher costs in creating new job openings than those in the clean sector. Consequently, the higher cost limits the number of vacancies the dirty sector can post, leading to fewer job opportunities in this sector for each skill type of worker, as reflected in lower job-finding rates observed in the data. The comparison of productivity parameters across worker skill types reveals that the dirty sector is more productive than the clean sector. Additionally, within each sector, high-skill workers have higher productivity than low-skill workers, as expected.

Panel A of Table 5 shows that the model closely matches the targeted moments in the commuting zone with the median unemployment rate. To further assess model fit, I examine how well the model predicts untargeted moments, including the sectoral employment share by education level and unemployment rates in that location. Panel B displays the data moments and their model-generated counterparts, showing that the model-generated moments closely fit the untargeted moments observed in the data.

Table 4: Parameters in the CZ with the Median Unemployment Rate

Definition	**Parameter**	**Value**	**Definition**	**Parameter**	**Value**
Vacancy Posting Cost (Sector-Worker Type)			Productivity (Sector-Worker Type)		
Clean-Low Skill	κ_c^l	0.0042			
Dirty-Low Skill	κ_d^l	1.1480	Dirty-Low Skill	z_d^l	1.93
Clean-High Skill	κ_c^h	0.0017	Clean-High Skill	z_c^h	2.02
Dirty-High Skill	κ_d^h	3.5231	Dirty-High Skill	z_d^h	3.79

Notes: This table lists the jointly calibrated parameters and their values in the commuting zone with the median unemployment rate.

Table 12 reports the remaining calibrated parameters: match-specific productivities, separation rates across commuting zones, and the base-level local amenities for high-skill and low-skill workers. The model's fit to targeted moments across commuting zones is illustrated in Figure 16 for the

Table 5: Model Fit in the CZ with the Median Unemployment Rate

	Data	Model		Data	Model
A.Targeted Moments					
Job-Finding Rate			**Wage Rate**		
Clean - Low Skill	0.78	0.78			
Dirty - Low Skill	0.18	0.18	Dirty - Low Skill	1.30	1.24
Clean - High-Skill	0.87	0.87	Clean - High Skill	1.95	2.04
Dirty - High-Skill	0.11	0.11	Dirty - High Skill	2.42	2.46
B.Untargeted Moments					
Sectoral Share			**Unemployment Rate**		
Low-Skill - Clean	0.850	0.852			
Low-Skill - Dirty	0.089	0.089	Low-Skill	6.10	5.89
High-Skill - Clean	0.939	0.936			
High-Skill - Dirty	0.042	0.044	High-Skill	1.98	2.00

Notes: This table compares the targeted and untargeted moments in the data with their corresponding values in the model for the commuting zone with the median unemployment rate.

unemployment rate, Figure 17 for the share of clean sector employment, and Figure 18 for relative wage comparisons. Generally, the model fits the targeted moments well across commuting zones, suggesting that the model accurately captures key labor market dynamics and sectoral distributions.

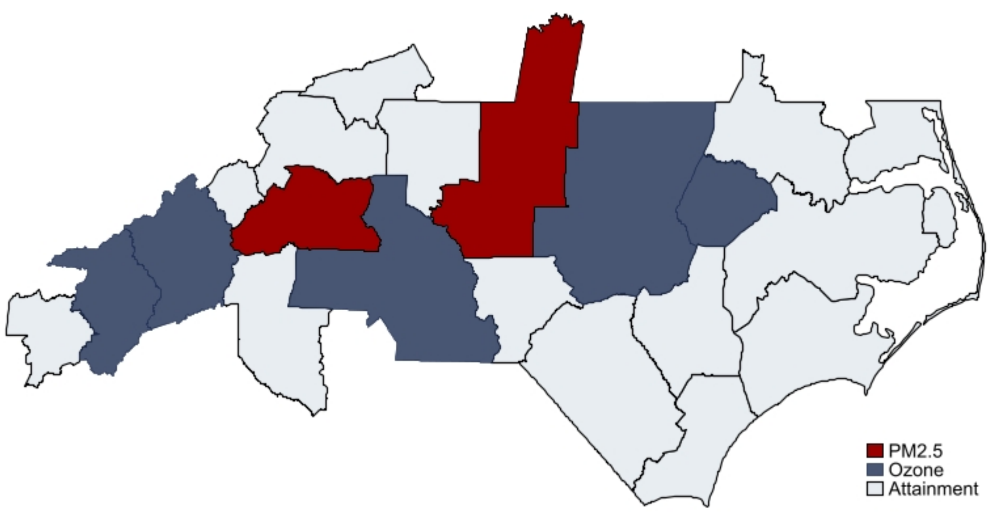
The productivity parameters reflect the productivity of sector-worker type matches across commuting zones, capturing variations in location-specific productivity. The table shows that the relationships between sectors and worker types previously discussed hold consistently across all commuting zones. Additionally, productivity values and the relative differences between parameters vary across zones, highlighting local differences in productivity dynamics. Other than location differences, another reason could be the industry composition of dirty and clean sectors. Understanding these productivity variations is important for assessing the impact of regulation, as they directly influence sector output and the unemployment value of workers across commuting zones.

Across commuting zones, high-skill workers generally have lower separation rates than low-skill workers in both sectors, indicating they are less likely to lose their jobs. Although no consistent trend emerges across all zones, an interesting pattern appears. When the separation rate in the dirty sector is lower (higher) than in the clean sector for high-skill workers, it also tends to be lower (higher) for low-skill workers in most commuting zones. This suggests that separation rates may be influenced by location- or sector-specific factors, such as industry composition, which affect both skill levels similarly within each zone.

The table also shows that base-level amenities vary significantly across commuting zones for high- and low-skill workers. The model results show a nuanced relationship between wages and base-level amenities that differs by skill level, as shown in Figure 19. For high-skill workers, the negative relationship suggests a compensating differential effect: high-skill workers are willing to give up some of their wages for higher amenities. In contrast, there is no significant relationship between wages and amenities for low-skill workers, indicating that amenities may not play a strong role in their location choice or wage determination. This could be due to several factors. One possible reason could be that low-skill workers may prioritize higher wages over amenities to meet basic living expenses, making them less likely to accept wage reductions in exchange for amenities. Overall, this divergence highlights the importance of evaluating the distributional welfare effects of place-based environmental policies that improve local quality of life while worsening local labor markets.

To evaluate the effects of the 1997 standards change on employment, unemployment, sectoral and spatial reallocation of the labor force, and welfare for both worker types, I calibrated the abatement parameters, Γ^p, for ozone and $PM_{2.5}$, to allow thee model reproduce the employment effects reported in Section 4. Specifically, I target an average decrease in low-skill employment of 12% in dirty sectors for commuting zones regulated for ozone and a 17% decrease in employment for those regulated for $PM_{2.5}$, using an equation analogous to the triple-difference design in Equation 2. Figure 4 shows the commuting zones by regulatory status. The blue zones are classified as regulated for ozone standards, the red zones are classified as $PM_{2.5}$ standards, and the light grays denote the attainment zones. [50]

Figure 4: Commuting Zones by Regulatory Status in North Carolina



Note: Figure shows the commuting zones classified as regulated. Five commuting zones contain counties regulated under ozone standards, the blue ones; manufacturing employment in these regulated counties represents, on average, 60% of the total manufacturing employment within their respective commuting zones. For counties regulated under $PM_{2.5}$ standards, the red ones, this share averages around 50%. Additionally, regulated counties account for 47% of North Carolina's population.

[50] In 2004, 19 counties were designated as nonattainment for ozone standards. These counties are located within five commuting zones: CZ 87 (Raleigh-Durham), CZ 91 (Asheville), CZ 123 (Jackson-Macon-Rabun-Swain Counties), CZ 138 (Charlotte-Gastonia-Concord), and CZ 146 (Rocky Mount). In 2005, three counties were designated as nonattainment for $PM_{2.5}$ standards within two commuting zones: CZ 246 (Hickory-Morganton-Lenoir) and CZ 248 (Greensboro-High Point-Danville-Burlington).

Assuming free mobility across commuting zones, I calibrated the abatement parameters, finding abatement rates of 0.25 for ozone and 0.34 for $PM_{2.5}$. These estimates indicate that polluting sectors in zones regulated for ozone reduce NOx and VOC emissions by 33%, while sectors regulated for $PM_{2.5}$ achieve a 52% reduction. This emission decrease aligns with the literature; for example, Shapiro and Walker (2018) reports a 60% reduction in air pollution emissions from U.S. manufacturing between 1990 and early 2000s, with emissions of regulated pollutants like nitrogen oxides and VOCs declining by an average of 35%, largely due to environmental regulations.

7 Effect of the 1997 Nonattainment Standards

I quantify the steady-state impact of the 1997 standards on various outcomes, comparing them to a benchmark scenario where no commuting zones are in nonattainment status and accounting for different levels of worker mobility. The main results are reported in Table 6. The first column displays the average effects for regulated commuting zones, while the second column shows the outcomes for nonregulated zones. The third and fourth columns further break down the effects for commuting zones regulated specifically for ozone and $PM_{2.5}$, respectively.

Panel A presents results for perfect worker mobility across commuting zones and sectors, reflecting an environment where workers can relocate freely in response to labor market changes. Panel B shows outcomes under restricted spatial mobility, where workers can switch between jobs within commuting zones but not move to other zones. Finally, Panel C represents a scenario with no mobility, where unemployed workers cannot change location or transition to the clean sector after losing a job in a dirty sector within commuting zones.[51] Each panel provides insights into changes in various outcomes, such as employment, unemployment rates, welfare, dirty sector production, and environmental damages across these different mobility restrictions.

Changes in Low-Skill Employment: Low-skill employment in dirty sectors drops by 8.58%, while employment in clean sectors increases by 1.41% in regulated zones after implementing regulation, in case of perfect mobility. These results suggest that regulations effectively discourage the dirty sectors, leading to a notable reduction in low-skill jobs within these sectors while shifting employment to the clean sectors, partially offsetting the employment losses in dirty sectors.

The differences in the decline of dirty sector employment between commuting zones regulated for ozone and $PM_{2.5}$ highlight the impact of stricter restrictions, as dirty sectors must meet higher abatement rates for $PM_{2.5}$. There is a larger decline in dirty sector employment in zones regulated for $PM_{2.5}$, 9.96%, compared to an 8.04% drop in zones regulated for ozone. The impact of stricter regulations is also evident in the increase in clean sector employment in regulated zones, suggesting that clean sectors may expand in response to tighter regulations, particularly where $PM_{2.5}$ standards apply.

The changes in low-skill employment in nonregulated commuting zones suggest that these areas

[51] I hold constant the vacancy posting of the clean sector at the benchmark scenario.

Table 6: Effect of the 1997 Standards in North Carolina Commuting Zones

	Regulated	**Nonregulated**	**Ozone**	**PM$_{2.5}$**
A.Perfect Mobility				
Employment (%)				
Clean-Low skill	1.41	1.15	0.64	3.32
Dirty-Low Skill	-8.58	4.97	-8.04	-9.96
Clean-High Skill	-0.53	-6.37	-2.10	3.39
Dirty-High Skill	-2.05	-8.53	-3.20	0.82
Unemployment Rate (p.p.)				
Low Skill	0.05	0.00	-0.01	0.14
High Skill	0.03	-0.02	0.03	0.04
Welfare (%)				
Total	0.04	-2.11	-0.17	0.56
Low Skill	-1.38	1.46	-0.97	-2.39
High Skill	0.20	-6.72	-1.31	3.96
Dirty Sector Production (%)	-6.70	2.68	-5.26	-10.29
Damages (%)	-8.51	0.22	-8.84	-7.70
B.No Spatial Mobility				
Employment (%)				
Clean-Low skill	2.79	-	1.72	5.46
Dirty-Low Skill	-7.04	-	-6.77	-7.71
Unemployment Rate (p.p.)				
Low Skill	0.76	-	0.63	1.03
Welfare (%)				
Total	-1.42	1.27	-1.03	-2.71
Low Skill	-3.47	2.61	-2.81	-5.25
High Skill	0.01	0.12	0.01	0.02
Dirty Sector Production (%)	-5.89	-	-4.65	-9.00
Damages (%)	-8.09	-2.99	-8.57	-6.90
C.No Mobility				
Unemployment Rate (p.p.)				
Low Skill	1.77	-	1.26	3.03
Welfare (%)				
Total	-4.08	1.27	-2.88	-7.08
Low Skill	-9.58	2.61	-7.98	-13.58

Note: Table 6 reports the main results. The first column displays the average effects for regulated commuting zones, while the second column shows the outcomes for nonregulated zones. The third and fourth columns further break down the effects for commuting zones regulated specifically for ozone and $PM_{2.5}$, respectively. Panel A presents results under conditions of perfect worker mobility across commuting zones and sectors, allowing workers to relocate in response to labor market changes freely. Panel B shows outcomes under restricted spatial mobility, where workers can switch between jobs within commuting zones but cannot move to other zones. Finally, Panel C represents a scenario with no mobility, where unemployed workers cannot change location or transition to the clean sector after losing a job in a dirty sector within commuting zones.

may experience indirect effects due to spillover or sectoral shifts. On average, low-skill employment rises by 1.15% in clean sectors and by 4.97% in dirty sectors. The increase in dirty sector employment may reflect a shift of pollution-intensive activities from regulated to nonregulated areas. Although the perfect mobility scenario allows for sectoral shifts, the larger increase in dirty sector employment within nonregulated zones is consistent with findings in the literature. Curtis et al. (2024) indicates that workers without a college education are more likely to transition from one dirty job to another.

The low-skill employment results from the no spatial mobility scenario reveal a smaller decline in dirty sector employment and a larger increase in clean sector employment within regulated zones. Comparing results from Panel A and Panel B suggests that, with perfect mobility, low-skill workers respond to regulation by reallocating to nonregulated zones. If workers preferred to stay within their commuting zones regardless of mobility restrictions, we would observe similar effects in both scenarios. This underscores the importance of labor mobility in mitigating the negative employment impacts of place-based environmental regulations.

Changes in Low-Skill Unemployment Rates: Worker mobility across commuting zones and sectors also plays a crucial role in mitigating the unemployment impacts of regulation. In Panel A, where mobility is unrestricted, the low-skill unemployment rate increases only slightly by 0.05 percentage points. In contrast, this rate rises more substantially to 0.76 percentage points under no spatial mobility and climbs further to 1.77 percentage points when both sectoral and spatial mobility are restricted. Without the ability to relocate across zones, low-skill workers face greater challenges adapting to the negative employment effects of regulation, as reflected in the higher unemployment rates. While some workers may transition within sectors, limited mobility leaves many without viable employment options within their zones. These effects are further amplified when sectoral shifts are particularly difficult for low-skill workers.

Changes in High-Skill Employment Rates: On average, high-skill employment in regulated zones declines slightly by 0.53% in clean sectors and by 2.05% in dirty sectors. However, the findings indicate that high-skill employment increases in commuting zones regulated for $PM_{2.5}$, with a 3.39% rise in clean sector employment and a 0.82% in dirty sectors. Conversely, both sectors in nonregulated and ozone-regulated zones experience a decrease in high-skill employment. Although there are significant changes in employment for high-skill workers, their unemployment rates remain relatively stable.

These findings reveal an interesting relocation pattern in high-skill workers' response to regulation. As discussed in the model results, high-skill workers are more sensitive to changes in amenities. The influx of low-skill workers into nonregulated areas, along with increased dirty sector production and associated damages, may encourage high-skill workers to move to zones regulated for $PM_{2.5}$. They tend to prefer $PM_{2.5}$-regulated zones over ozone-regulated ones, despite reductions in damages in both, due to the relatively higher value of base-level amenities in $PM_{2.5}$-regulated areas. High-skill workers are more likely to move to areas with better amenity values, which improved after the regulation. To gain deeper insights, I will examine the spatial distribution of labor.

Changes in Dirty Sector Production and Damages from Air Pollution: With unrestricted mobility, dirty sector production decreases by 6.70% in regulated zones but increases by 2.68% in nonregulated zones, likely due to the shift of pollution-intensive activities and reallocation of workers to areas with fewer restrictions, as discussed in the literature Henderson (1996), Greenstone (2002). In contrast, under no spatial mobility, dirty sector production in regulated zones decreases by 5.89%, with no effect on production in nonregulated zones. As indicated by the comparison between zones regulated for ozone and $PM_{2.5}$, stricter regulations lead to larger reductions in dirty sector production.

The decrease in dirty sector production, along with the reduction in emission intensity due to abatement efforts, impacts air pollution damages by reducing pollutant emission levels. In nonregulated zones, damages decrease on average under no spatial mobility, as there is no spillover of dirty sector activities. However, under perfect mobility, damages in nonregulated zones increase slightly, likely due to the relocation of dirty sector activities and an inflow of workers into these areas. Since nonregulated zones do not implement abatement technologies, changes in damages are driven solely by shifts in dirty sector production levels. Thus, with perfect mobility, the increase in dirty sector production in nonregulated zones results in higher local damages.

Changes in Welfare Low-skill workers in regulated zones experience welfare losses that vary with their ability to relocate across zones or shift between sectors. Welfare decreases by 1.38% with perfect mobility, by a larger margin of 3.47% with no spatial mobility, and even more sharply, by 9.58% when both spatial and sectoral mobility are restricted. These results suggest that the inability to switch sectors or relocate intensifies the negative impacts of regulation. While switching sectors or relocating across zones may offset some welfare losses, the regulatory impact on employment and sectoral shifts still imposes a welfare cost on low-skill workers. Moreover, the stricter regulations impose higher welfare losses, as shown in the regulated zones for $PM_{2.5}$.

The welfare of low-skill workers in nonregulated commuting zones rises significantly by 2.61% when spatial mobility is restricted, compared to an increase of only 1.46% with perfect mobility. This result is quite intuitive: with restricted mobility, low-skill workers in nonregulated zones benefit from enhanced amenities without the influx of additional workers. In contrast, when mobility is unrestricted, the inflow of workers into nonregulated areas has two distinct effects. On the one hand, the dirty sector, which has higher productivity, creates new job vacancies, increasing employment opportunities. On the other hand, the influx of new workers intensifies competition for these vacancies. Additionally, the increase in dirty sector production and associated damages reduces the overall value of amenities in nonregulated zones.

The inflow of low-skill workers into nonregulated zones leads to welfare losses for high-skill workers. Conversely, high-skill workers may experience welfare gains by reallocating to zones regulated for $PM_{2.5}$. Since low-skill and high-skill workers do not compete for the same job openings, the negative welfare effects do not come from labor market conditions; they may result from changes in amenities and housing costs.

7.1 The Spatial Effect of the 1997 Standards

I examine the changes across commuting zones to evaluate the spatial distribution of the 1997 standards' effects on dirty sector production, amenities, employment reallocation, and welfare.

Figure 5a shows how dirty sector production changes when spatial mobility is restricted, while Figure 5b illustrates the changes when spatial mobility is allowed. In the absence of spatial mobility, the negative impact of regulation on dirty sector production is primarily concentrated in regulated zones. In contrast, Figure 5b indicates that when spatial mobility is permitted, non-regulated zones experience varying degrees of production increases, with commuting zones highlighted in yellow showing the most significant rises, exceeding 13%. Additionally, Figure 5b demonstrates that regulated commuting zones experience a greater reduction in dirty sector production when spatial mobility is allowed, compared to the scenario without spatial mobility.

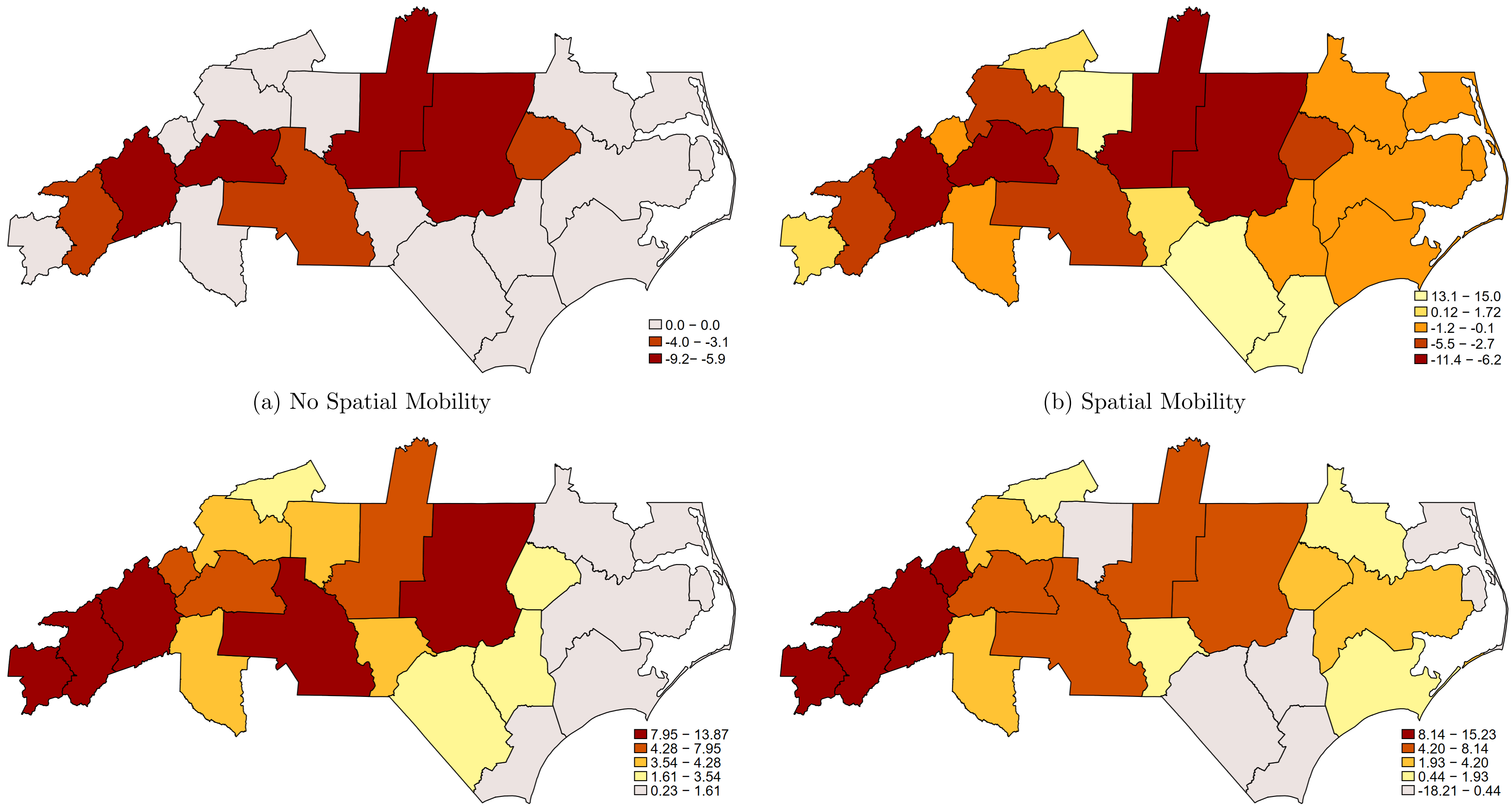
Changes in amenities for both scenarios are illustrated in Figures 5c and 5d. In the scenario without spatial mobility, the changes in amenities are driven by a reduction in dirty sector production and lower emission intensities, which result from the implementation of abatement technologies in regulated commuting zones. These regulated zones experience greater improvements in amenities, with most ozone-regulated areas seeing increases of over 8%, while areas regulated for $PM_{2.5}$ show improvements ranging from 4% to 8%. Furthermore, nonregulated commuting zones that are closer to regulated areas tend to experience more significant improvements in amenities, which underscores the importance of considering cross-border air transportation when assessing the welfare effects of regulations.

Figure 5d shows how the reallocation of labor and activities from the dirty sector impacts amenities, particularly in nonregulated areas. This reallocation intensifies concerns over emission leakage, as commuting zones that experience growth in dirty sector production face notable declines in amenities, with reductions reaching up to 15%. Conversely, these reallocations cause further improvement in amenities in regulated zones as a result of shifting economic activities.

Figure 6 shows the percentage change in employment across commuting zones, categorized by sector (clean vs. dirty) and skill level (high vs. low). Specifically, Figure 6a illustrates changes in high-skill employment within clean sectors, while Figure 6b focuses on high-skill employment in dirty sectors. High-skill employment increases in both sectors for most regulated zones, with a greater rise in clean sector employment. Only one regulated zone, commuting zone 123, experiences a significant decline in high-skill employment. This zone has the highest base-level local amenities but the lowest productivity among regulated zones, as well as the lowest share of high-skill employment. Consequently, it experiences a large employment decrease from an already small baseline. This suggests that high-skill workers are more likely to relocate from zones with increased dirty sector production and associated damages to zones experiencing improvements in amenities.

Figure 6c and 6d display the percentage change in low-skill employment in clean and dirty sectors, respectively. While all nonregulated zones experience a decrease in low-skill employment within dirty sectors, changes in clean sector employment vary across zones. Ozone-regulated commuting zones, including the Charlotte MSA, Durham-Raleigh MSA, and Asheville, also show

Figure 5: (Top) Change in Dirty Sector Production (%); (Bottom) Change in Amenities (%)



(a) No Spatial Mobility

(b) Spatial Mobility

(c) No Spatial Mobility

(d) Spatial Mobility

Note: This figure illustrates the spatial effects of the 1997 standards on dirty sector production and amenities across commuting zones. The top row shows the percentage change in dirty sector production, with Panel (a) displaying changes under no spatial mobility and Panel (b) under spatial mobility. In the production maps, darker colors indicate a larger decrease in dirty sector production, while lighter colors represent smaller decreases. The bottom row represents the percentage change in amenities, with Panel (c) showing no spatial mobility and Panel (d) allowing for spatial mobility. For the amenities maps, darker colors correspond to higher improvements in amenities. These comparisons highlight how mobility restrictions impact both dirty sector production and the associated amenities in regulated and nonregulated zones.

a decrease in clean sector employment, whereas other regulated zones display an increase. Low-skill workers are more likely to relocate to zones with increased dirty sector production. Some regions experience a notable rise(decline) in high-skill employment while simultaneously witnessing a decline(rise) in low-skill employment within dirty sectors. Overall production in dirty sectors within these commuting zones yields mixed outcomes, as seen in areas like the Wilmington MSA and Greenville MSA.

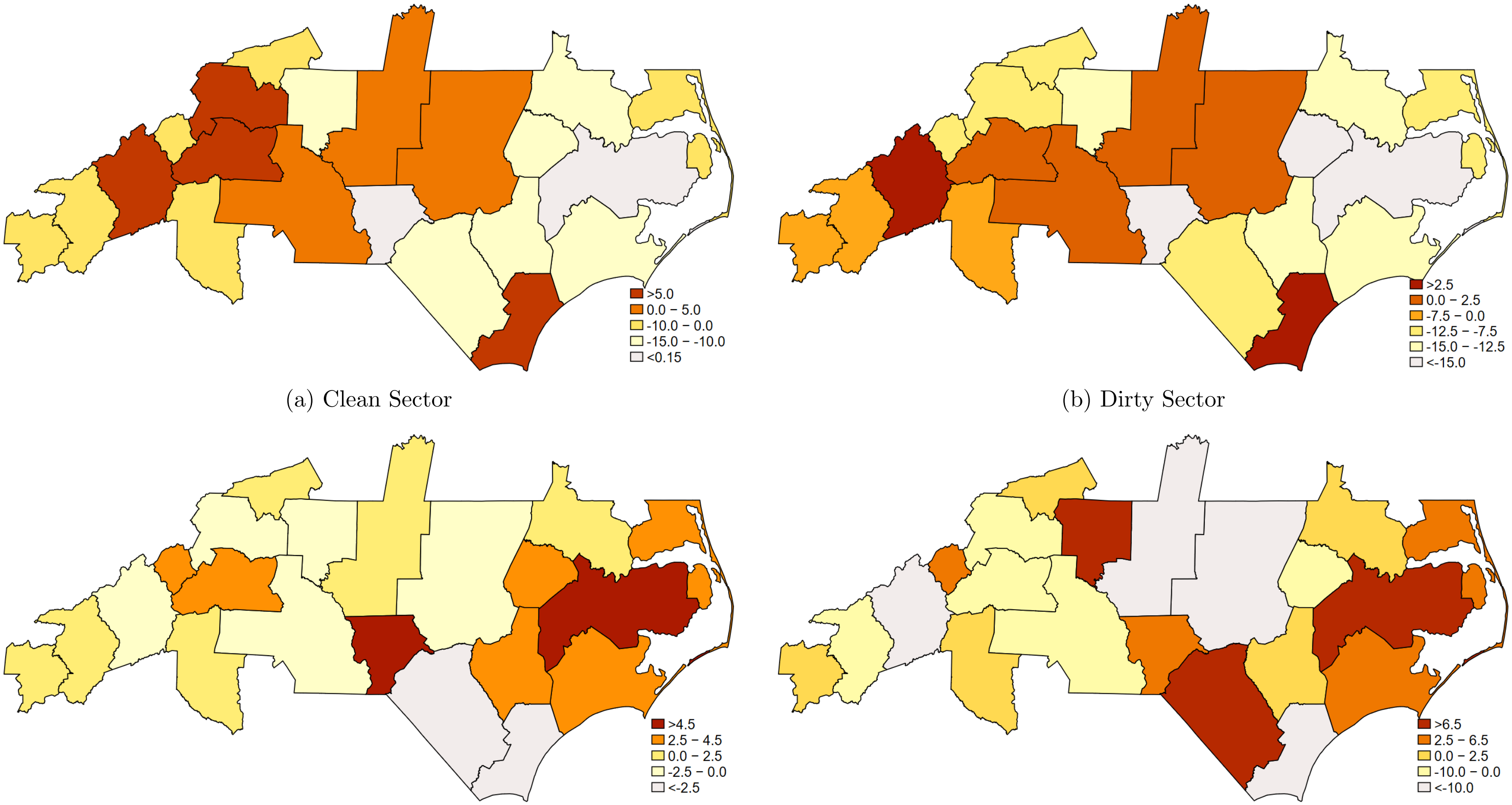
Finally, Figure 7 shows the changes in welfare for both high- and low-skill workers, reflecting the combined impact of shifting labor market conditions and amenities. This figure highlights how welfare outcomes vary based on skill level, shaped by the spatial distribution of employment and amenities across commuting zones under the 1997 standards. While high-skill workers experience welfare gains in most regulated zones, they are worse off in non-regulated places due to lower amenity levels, as shown in Figure 7a. High-skill workers who move to nonregulated zones experience significant improvements in amenities, as these locations also offer higher wages due to higher productivity. The trade-off between higher wages and better amenities diminishes for high-skill workers.

On the other hand, low-skill workers are generally worse off in regulated zones, despite improved amenities, due to the adverse effects of regulation on dirty sector production. Although some low-skill workers migrate away from regulated zones, reducing competition for vacancies in dirty sectors, they are less likely to find a job in dirty sectors because of the decrease in vacancy openings. The probability of finding a job in the sectors that pay higher wages decreases, leading to a decrease in welfare.

Low-skill workers can mitigate these negative welfare effects by relocating to nonregulated zones. In these areas, they typically experience an improvement in welfare due to increased job opportunities in the dirty sector. While nonregulated zones often see a reduction in amenities, the rise in employment within dirty sectors tends to offset this decline, providing low-skill workers with a net welfare gain in many cases. The welfare gains also suggest that increasing job opportunities in dirty sectors helps offset the negative effects of the inflow of new workers, which creates congestion in the labor market. The increased activities in dirty sectors absorb much of this inflow, mitigating the competitive pressures that might otherwise decrease wages or reduce job-finding rates, ultimately contributing to improved welfare outcomes for low-skill workers in nonregulated zones.

Overall, these findings suggest that low-skill workers' ability to reduce the negative welfare impacts of place-based regulation depends on how easily they can move across commuting zones and sectors. Increased job opportunities, whether in clean sectors or nonregulated areas, play a key role in offsetting the adverse welfare effects of regulation. Mobility allows low-skill workers to adjust to changes in local labor markets, helping them find areas with new job opportunities and, in turn, lessen the welfare losses caused by place-based regulations.

Figure 6: (Top) Change in High Skill Employment (%); (Bottom) Change in Low Skill Employment (%)



(a) Clean Sector

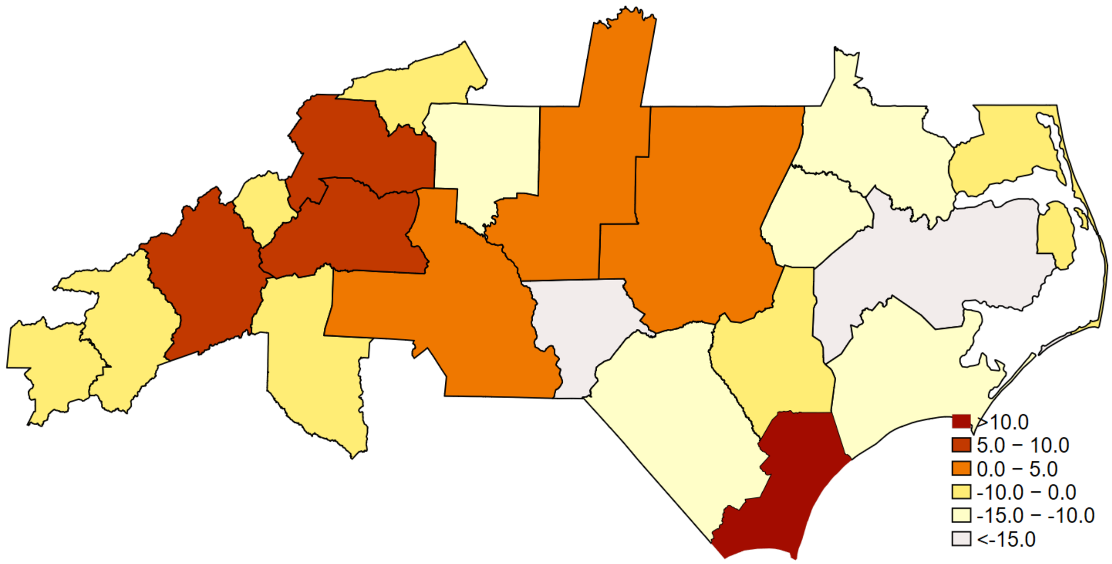
(b) Dirty Sector

(c) Clean Sector

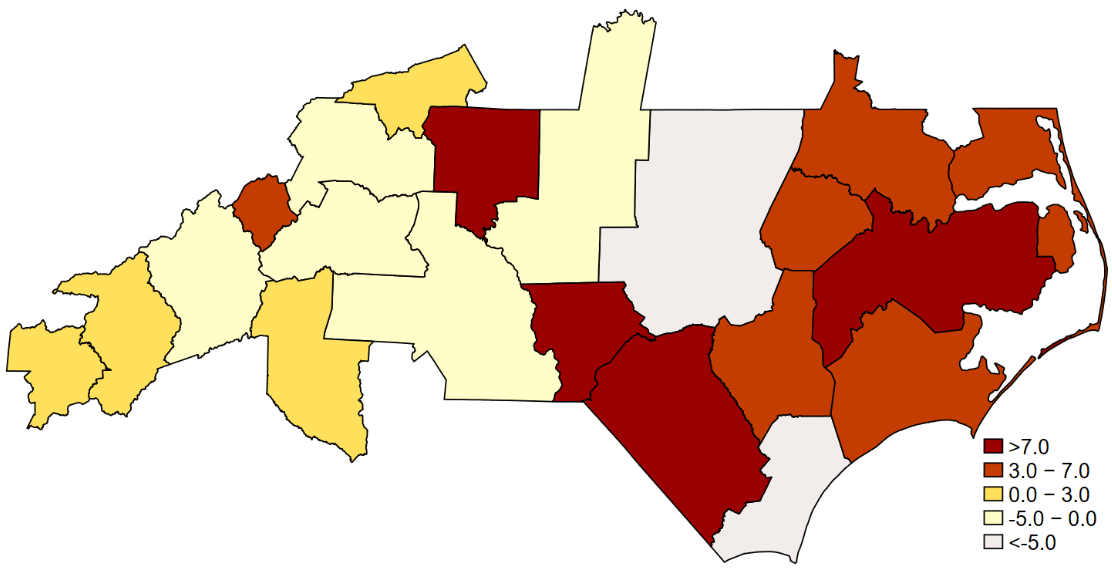
(d) Dirty Sector

Note: This figure displays the percentage change in employment across commuting zones, separated by sector (clean vs. dirty) and skill level (high vs. low). The top row shows changes in high-skill employment, with Panel (a) illustrating employment changes in clean sectors and Panel (b) in dirty sectors. The bottom row shows changes in low-skill employment, with Panel (c) representing clean sectors and Panel (d) dirty sectors. In each map, the darkest color indicates positive changes in employment, while lighter colors represent increasingly negative employment effects. These maps provide a visual comparison of employment shifts across skill levels and sector types in response to the 1997 standards.

Figure 7: Changes in Total Welfare



(a) High-Skill



(b) Low-Skill

Note: This figure illustrates the changes in total welfare across commuting zones, separated by skill level. Panel (a) shows the welfare changes for high-skill workers, while Panel (b) displays the welfare changes for low-skill workers. Darker colors indicate positive welfare changes, while lighter colors represent negative welfare changes. This visualization highlights the spatial variation in welfare impacts across skill levels in response to the 1997 standards, allowing for a comparison of how regulatory effects differ between high-skill and low-skill workers.

8 Conclusion

I developed a novel framework to evaluate the distributional welfare impacts of place-based environmental regulations that target pollution-intensive sectors in polluted areas. First, I assessed the causal effect of the 1997 National Air Quality Standards (NAAQS) on employment for college- and non-college-educated workers. While regulations of either ozone or $PM_{2.5}$ alone did not significantly impact college-educated employment, non-college employment declined by 12% due to ozone regulation and by 17% due to $PM_{2.5}$ regulation.

Then, I developed a general equilibrium spatial model of labor market search and matching that incorporates market frictions and accounts for the atmospheric transport of air pollutants. The model was used to evaluate the effects of the 1997 NAAQS on workers in North Carolina.

My findings show that the 1997 standards led to a significant decrease in low-skill jobs in pollution-intensive industries in regulated areas. At the same time, there was a slight increase in employment in the clean sectors of those areas. The impact was particularly pronounced in regions regulated for $PM_{2.5}$, demonstrating the effects of stricter pollution control measures. Furthermore, nonregulated areas experienced spillover effects, attracting dirty sector employment from regulated areas. High-skill employment tends to increase in regulated areas as high-skill workers migrate from non-regulated zones to these areas due to enhanced amenities.

Mobility constraints played a key role in shaping these outcomes. While the unemployment rate for low-skill workers increased only slightly with unrestricted mobility, it rose significantly when mobility was restricted. This highlights the importance of labor mobility in mitigating the negative effects of regulation on employment. My findings also illustrate how production in dirty sectors can move from regulated areas to unregulated ones leading to emission leakage and increased air pollution damages caused in nonregulated areas.

The welfare impacts of regulation are uneven across skill levels and regions. Low-skill workers in regulated zones faced welfare losses, exacerbated by mobility restrictions, while those in nonregulated zones saw gains due to new job opportunities in pollution-intensive sectors. On the other hand, high-skill workers benefited from amenity improvements in regulated zones but faced welfare declines in nonregulated areas due to increased pollution.

Overall, these findings suggest that improving labor mobility—both across sectors and commuting zones—can significantly reduce negative welfare effects of regulation, especially for low-skill workers. Policies that promote clean sector employment, such as those outlined in the Inflation Reduction Act, can support this transition. However, it may be essential to focus on improving mobility and providing opportunities for workers to switch between sectors to ensure equitable outcomes. This is particularly important for low-skill workers, who often have limited opportunities to transition into green jobs.

References

Aguilar-Gomez, S., H. Dwyer, J. Graff Zivin, and M. Neidell (2022). This is air: The "nonhealth" effects of air pollution. Annual Review of Resource Economics 14(1), 403–425.

Aldeco, L., L. Barrage, and M. A. Turner (2019). Equilibrium particulate exposure. IGC Working Paper, C–89451.

Athey, S. and G. W. Imbens (2022). Design-based analysis in difference-in-differences settings with staggered adoption. Journal of Econometrics 226(1), 62–79.

Aubert, D. and M. Chiroleu-Assouline (2019). Environmental tax reform and income distribution with imperfect heterogeneous labour markets. European Economic Review 116, 60–82.

Balistreri, E. J. (2002). Operationalizing equilibrium unemployment: a general equilibrium external economies approach. Journal of Economic Dynamics and Control 26(3), 347–374.

Becker, R. and V. Henderson (2000). Effects of air quality regulations on polluting industries. Journal of political Economy 108(2), 379–421.

Becker, R. A. (2005). Air pollution abatement costs under the clean air act: evidence from the pace survey. Journal of environmental economics and management 50(1), 144–169.

Becker, R. A. and J. V. Henderson (2001). Costs of air quality regulation. Behavioral and distributional effects of environmental policy, Carraro, Carlo and Metcalf, Gilbert E, eds., 159–186.

Berman, E. and L. T. Bui (2001). Environmental regulation and productivity: evidence from oil refineries. Review of economics and statistics 83(3), 498–510.

Bishop, K. C., J. D. Ketcham, and N. V. Kuminoff (2023). Hazed and confused: the effect of air pollution on dementia. Review of Economic Studies 90(5), 2188–2214.

Borusyak, K., X. Jaravel, and J. Spiess (2021). Revisiting event study designs: Robust and efficient estimation. arXiv preprint arXiv:2108.12419.

Callaway, B. and P. H. Sant'Anna (2021). Difference-in-differences with multiple time periods. Journal of econometrics 225(2), 200–230.

Currie, J., J. Voorheis, and R. Walker (2023). What caused racial disparities in particulate exposure to fall? new evidence from the clean air act and satellite-based measures of air quality. American Economic Review 113(1), 71–97.

Curtis, E. M. (2018). Who loses under cap-and-trade programs? the labor market effects of the nox budget trading program. Review of Economics and Statistics 100(1), 151–166.

Curtis, E. M. (2020). Reevaluating the ozone nonattainment standards: Evidence from the 2004 expansion. Journal of Environmental Economics and Management 99, 102261.

Curtis, E. M., L. O'Kane, and R. J. Park (2024). Workers and the green-energy transition: Evidence from 300 million job transitions. Environmental and Energy Policy and the Economy 5(1), 127–161.

De Chaisemartin, C. and X. d'Haultfoeuille (2024). Difference-in-differences estimators of intertemporal treatment effects. Review of Economics and Statistics, 1–45.

De Chaisemartin, C. and X. d'Haultfoeuille (2020). Two-way fixed effects estimators with heterogeneous treatment effects. American economic review 110(9), 2964–2996.

De Chaisemartin, C. and X. D'haultfœuille (2023). Two-way fixed effects and differences-in-differences estimators with several treatments. Journal of Econometrics 236(2), 105480.

Deryugina, T., G. Heutel, N. H. Miller, D. Molitor, and J. Reif (2019). The mortality and medical costs of air pollution: Evidence from changes in wind direction. American Economic Review 109(12), 4178–4219.

Dorn, D. (2009). Essays on inequality, spatial interaction, and the demand for skills. Dissertation (3613).

Fernández Intriago, L. A. (2019). Carbon taxation, green jobs, and sectoral human capital. Technical report, Working Paper, Arizona State University.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. Journal of econometrics 225(2), 254–277.

Greenstone, M. (2002). The impacts of environmental regulations on industrial activity: Evidence from the 1970 and 1977 clean air act amendments and the census of manufactures. Journal of political economy 110(6), 1175–1219.

Greenstone, M., J. A. List, and C. Syverson (2012). The effects of environmental regulation on the competitiveness of us manufacturing. Technical report, National Bureau of Economic Research.

Hafstead, M. A. and R. C. Williams III (2018). Unemployment and environmental regulation in general equilibrium. Journal of Public Economics 160, 50–65.

Hafstead, M. A., R. C. Williams III, and Y. Chen (2022). Environmental policy, full-employment models, and employment: A critical analysis. Journal of the Association of Environmental and Resource Economists 9(2), 199–234.

Henderson, J. V. (1996). Effects of air quality regulation. The American Economic Review, 789–813.

Hollingsworth, A., T. Jaworski, C. Kitchens, and I. Rudik (2024). Economic geography and air pollution regulation in the united states.

Kahn, M. E. and E. T. Mansur (2013). Do local energy prices and regulation affect the geographic concentration of employment? Journal of Public Economics 101, 105–114.

Kline, P. and E. Moretti (2013). Place based policies with unemployment. American Economic Review 103(3), 238–243.

Kuhn, M., I. Manovskii, and X. Qiu (2021). The geography of job creation and job destruction. Technical report, National Bureau of Economic Research.

Morehouse, J. M. (2021). Carbon taxes in spatial equilibrium.

Muller, N. Z. and R. Mendelsohn (2007). Measuring the damages of air pollution in the united states. Journal of Environmental Economics and Management 54(1), 1–14.

Muller, N. Z. and R. Mendelsohn (2009). Efficient pollution regulation: getting the prices right. American Economic Review 99(5), 1714–1739.

Muller, N. Z., R. Mendelsohn, and W. Nordhaus (2011). Environmental accounting for pollution in the united states economy. American Economic Review 101(5), 1649–1675.

Nordhaus, W. (2008). A question of balance: Weighing the options on global warming policies. Yale University Press.

Phelan, C. and A. Trejos (2000). The aggregate effects of sectoral reallocations. Journal of Monetary Economics 45(2), 249–268.

Pissarides, C. A. (2000). Equilibrium unemployment theory. MIT press.

Roback, J. (1982). Wages, rents, and the quality of life. Journal of political Economy 90(6), 1257–1278.

Rosen, S. (1979). Wage-based indexes of urban quality of life. Current issues in urban economics, 74–104.

Roth, J., P. H. Sant'Anna, A. Bilinski, and J. Poe (2023). What's trending in difference-in-differences? a synthesis of the recent econometrics literature. Journal of Econometrics 235(2), 2218–2244.

Rudik, I., G. Lyn, W. Tan, and A. Ortiz-Bobea (2022). The economic effects of climate change in dynamic spatial equilibrium.

Saiz, A. (2010). The geographic determinants of housing supply. The Quarterly Journal of Economics 125(3), 1253–1296.

Sant'Anna, P. H. (2023). Triple differences research designs at causal solutions. https://www.youtube.com/watch?v=LTuBEwASEJQ.

Schulz, B. (2024). Labor market dynamics with sorting. Journal of Economic Dynamics and

Control 158, 104776.

Shapiro, J. S. and R. Walker (2018). Why is pollution from us manufacturing declining? the roles of environmental regulation, productivity, and trade. American Economic Review 108(12), 3814–3854.

Shimer, R. (2013). A framework for valuing the employment consequences of environmental regulation. Work. Pap., Dep. Econ., Univ. Chicago.

Sun, L. and S. Abraham (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. Journal of econometrics 225(2), 175–199.

US Environmental Protection Agency (1999). The benefits and costs of the clean air act 1990 to 2010. Technical Report EPA-410-R-99-001, Final Report to the US Congress.

Walker, W. R. (2011). Environmental regulation and labor reallocation: Evidence from the clean air act. American Economic Review 101(3), 442–447.

Walker, W. R. (2013). The transitional costs of sectoral reallocation: Evidence from the clean air act and the workforce. The Quarterly journal of economics 128(4), 1787–1835.

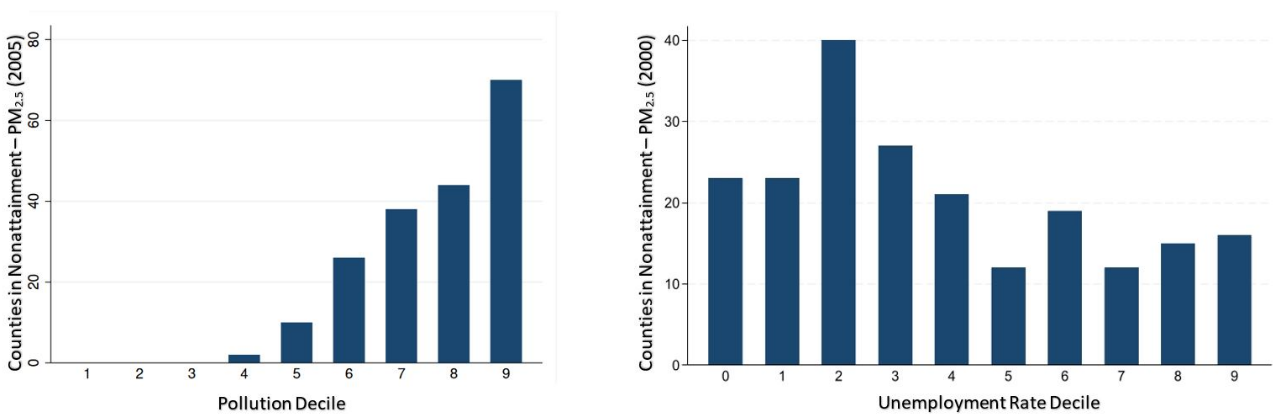
Appendix A

Appendix A.I

The left panel of Figure 8 illustrates the spatial variation in the number of counties regulated for $PM_{2.5}$ standards in 2005 across particulate matter pollution deciles. Areas with higher pollution levels are more likely to be subject to environmental regulations. In addition, the right panel of Figure 8 shows the number of counties regulated for $PM_{2.5}$ across unemployment rate deciles in 2000. Prior to the implementation of these regulations, 72% of nonattainment counties had unemployment rates below the national average.

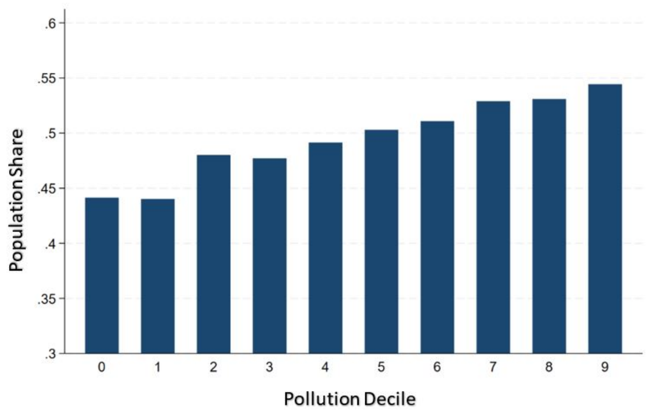
Furthermore, Figure 9 depicts the distribution of the population share with a high school degree or lower across pollution deciles in 2000. The figure shows that areas with higher pollution levels generally have a larger proportion of individuals with lower educational attainment. Specifically, there is a ten percentage point difference in the population share between the lowest and highest pollution deciles.

Figure 8: The number of nonattainment counties across pollution and unemployment rate deciles.



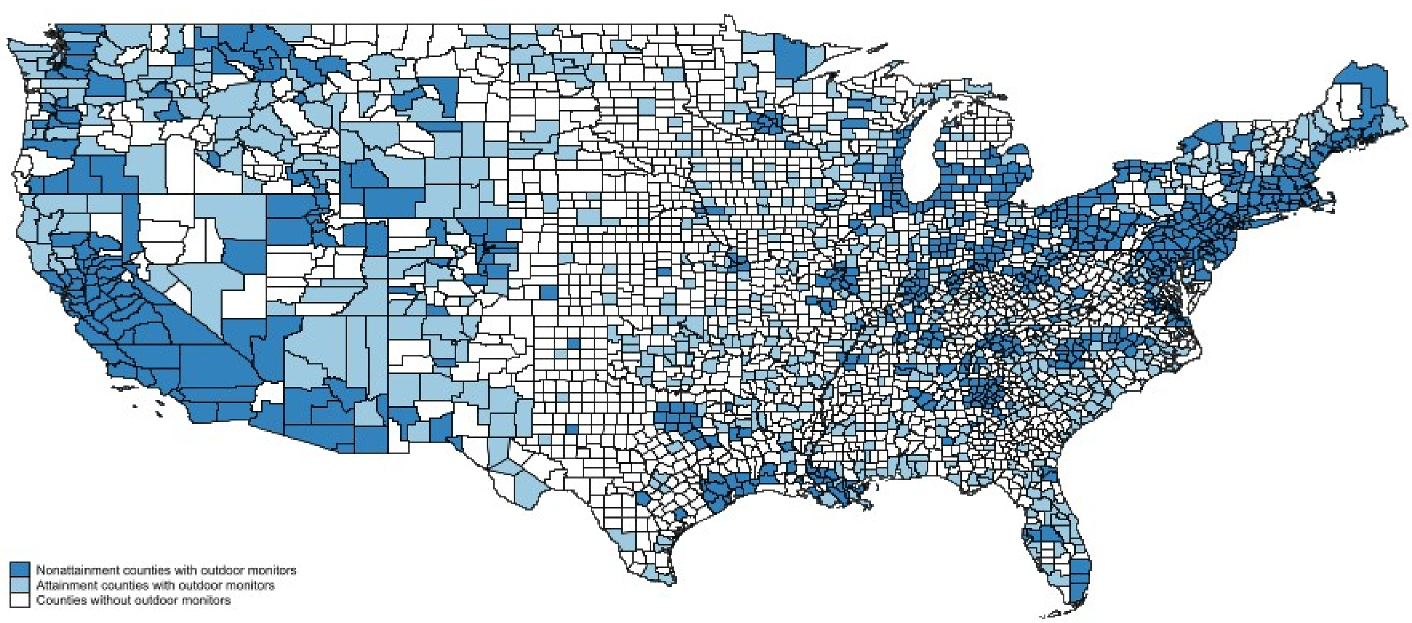
Note: The left panel shows the number of counties regulated for $PM_{2.5}$ standards in 2005 across particulate matter pollution deciles. The right panel displays the number of regulated counties for $PM_{2.5}$ across unemployment rate deciles in 2000. Before the regulation, 72% of nonattainment counties had unemployment rates below the national average. Source: Currie et al. (2023) for the left panel and U.S. Bureau of Labor Statistics, The Local Area Unemployment Statistics (LAUS) program, and EPA Green Book for the right panel.

Figure 9: Distribution of Population with High-School Degree or Below by Pollution Decile (PM2.5) in 2000



Note: The figure shows the distribution of the population share with less than a college degree in counties across pollution deciles in 2000. Source: EPA Green Book and Decennial Census

Figure 10: Counties with and without outdoor monitors



The figure shows the attainment (light blue) and nonattainment (dark blue) counties (white) that had annual concentration values collected by outdoor monitors in 2003 and counties that did not have a concentration value in 2003. The source is the EPA's Air Data 2003 annual concentration by monitors file.

Appendix A.II

Table 7: Percentage of Permits Held by Sector

	Estimation Sample		U.S.	
Share of Permits	VOC / NOx	$PM_{2.5}$	VOC / NOx	$PM_{2.5}$
Agriculture, Forestry, Fishing and Hunting	0.56	0.60	0.38	0.73
Mining, Quarrying, and Oil and Gas Extraction	24.54	18.90	32.22	23.78
Utilities	7.47	6.04	6.13	4.72
Construction	0.64	0.72	0.45	0.68
Manufacturing	41.70	51.28	33.75	43.07
Wholesale Trade	3.98	5.68	2.92	5.61
Retail Trade	0.57	0.54	2.30	1.82
Transportation and Warehousing	3.56	2.15	7.29	3.88
Information	4.51	0.53	2.52	0.95
Finance, Insurance and Real Estate	0.42	0.36	1.08	1.55
Business and Repair Services	12.05	13.22	10.97	13.21
# of Permits	34,159	20,702	256,533	143,476

Note: The table shows the percentage of permits held by sectors in the estimation sample and in the U.S. for contributors to ozone and fine particulate matter ($PM_{2.5}$). Permits in Mining, Quarrying, and Oil and Gas Extraction are concentrated in four states: Louisiana, Colorado, Oklahoma, and Montana. Plants in these states hold nearly 74% of permits for ozone contributors, while plants in Louisiana, Colorado, and Montana hold 57.72% of permits for $PM_{2.5}$.

Appendix A.III

To estimate population, labor force distribution by education level, and housing costs at the 2000 commuting zone level, I follow the methodology outlined in Dorn (2009) for 1990 commuting zones. The key step in this approach is calculating the probability, α_{jk}, that a resident in PUMA j resides in commuting zone k in 2000, for each j=1,...,2071 and each k=1,...,709. The probability α_{jk} is defined as:

$$\alpha_{jk} = \sum_{c=1}^{C} \frac{r_{jc}}{r_j} \frac{r_{ck}}{r_c} \quad \text{where } c = 1, \ldots, 3143$$

where c indicates counties, r_j is the number of residents in PUMA j, r_c is the number of residents in county c, r_{jc} is the number of residents in the overlap between PUMA j and county c, and r_{ck} is the number of residents in the overlap between county c and CZ k.

Since counties match to commuting zones one-to-one by definition, the second term is either zero or one. To construct the first term, I use the *ASCII* file from the Census Bureau, which provides population counts for each PUMA-county overlap in 2000.

To map the 2000 Census microdata to commuting zones (CZs), I replicate each individual observation $n = 1, ..., N$ by creating 709 identical observations. The only difference between these new observations and the original is the adjustment to the person weights, ω_n. The original person weights are adjusted according to:

$$\omega_{nk} = \omega_n * \alpha_{jk} \quad \text{where } k = 1, \ldots, 709$$

If a PUMA and commuting zone do not overlap, meaning α_{jk} =0, the corresponding observations are dropped. This method effectively splits an individual across multiple commuting zones when their PUMA is matched to more than one commuting zone.

Appendix B

Appendix B.I

Table 8: Sectoral Composition of Employment in 2001

	Estimation Sample			U.S.		
	(1)	(2)	(3)	(4)	(5)	(6)
Sectors	Share of Sectors	College Employment	High-School and Below Employment	Share of Sectors	College Employment	High-School and Below Employment
Agriculture, Forestry, Fishing and Hunting	0.008	0.126	0.633	0.009	0.124	0.649
Mining, Quarrying, and Oil and Gas Extraction	0.005	0.168	0.521	0.005	0.214	0.474
Utilities	0.005	0.417	0.261	0.007	0.440	0.238
Construction	0.067	0.134	0.561	0.055	0.160	0.530
Manufacturing	0.147	0.182	0.501	0.143	0.206	0.485
Wholesale Trade	0.051	0.248	0.420	0.049	0.297	0.378
Retail Trade	0.067	0.129	0.559	0.103	0.175	0.503
Transportation and Warehousing	0.031	0.147	0.523	0.038	0.190	0.475
Information	0.013	0.407	0.249	0.031	0.484	0.216
Finance, Insurance and Real Estate	0.057	0.349	0.312	0.064	0.415	0.271
Business and Repair Services	0.550	0.309	0.362	0.497	0.347	0.337
Share of Total Employment		0.261	0.415		0.297	0.388

Note: The table presents the sectoral and educational composition of employment in the estimation sample and the U.S. Columns (1) and (4) display the share of sectors in total employment. Columns (2) and (5) show the share of college graduates within sector employment, while Columns (3) and (6) indicate the share of high school graduates and below.

Table 9: Summary Statistic Before the Regulation for all Educational Levels (2001)

	Attainment		Switch into Nonattainment		Nonattainment	
County Population (Average)	87,981		105,542		343,346	
	Nonpolluting	Polluting	Nonpolluting	Polluting	Nonpolluting	Polluting
Panel A: All Sample						
Employment (Median)	334	544	352	684	324	982
Average Monthly Earnings	2,233	2,776	2,367	3,093	2,726	3,357
Hiring Rate	0.16	0.11	0.15	0.09	0.15	0.11
Separation Rate	0.16	0.12	0.16	0.10	0.15	0.11
Total Employment	8,685,444	3,725,048	3,728,670	2,430,348	42,024,360	30,335,438
Panel B: College and Above						
Average Monthly Earnings	3,222	3,968	3,508	4,450	3,939	4,711
Hiring Rate	0.13	0.09	0.13	0.07	0.11	0.08
Separation Rate	0.14	0.11	0.13	0.09	0.12	0.10
Total Employment	1,733,883	912,294	769,989	653,781	11,052,300	9,513,621
Panel C: High School and Below						
Average Monthly Earnings	1,971	2,446	2,059	2,693	2,226	2,845
Hiring Rate	0.14	0.10	0.13	0.08	0.12	0.09
Separation Rate	0.14	0.11	0.14	0.10	0.12	0.10
Total Employment	2,998,279	1,315,952	1,280,818	853,039	13,020,716	9,368,125
Panel D: Some College						
Average Monthly Earnings	2,320	2,858	2,455	3,142	2,751	3,377
Hiring Rate	0.13	0.10	0.13	0.08	0.12	0.09
Separation Rate	0.14	0.11	0.14	0.09	0.12	0.10
Total Employment	2,333,447	1,071,040	991,498	676,005	11,029,200	8,251,164
# of County x Sector	9,729	2,589	4,238	1,229	25,185	8,549

Appendix B.II

The marginal effect of $PM_{2.5}$ regulation on units that are regulated for both standards:

The idea to identify the effect of $PM_{2.5}$ on the group regulated for both pollutants is to compare the outcome evolution of groups that are treated and not treated by the $PM_{2.5}$ standards and that were regulated for ozone at the same time.

The first additional assumption is **the restriction on the effect of the ozone standards**, which means the effect of the ozone treatment evolves over time in the same way in every group. For all $t \geq 2004$,

$$\mathrm{E}[Y_t(2004,0) - Y_{t-1}(2004,0)|C = (2004,2005), \mathcal{L} = P] - \mathrm{E}[Y_t(2004,0) - Y_{t-1}(2004,0)|C = (2004,2005), \mathcal{L} = NP]$$
$$=$$
$$\mathrm{E}[Y_t(2004,0) - Y_{t-1}(2004,0)|C = (2004,0), \mathcal{L} = P] - \mathrm{E}[Y_t(2004,0) - Y_{t-1}(2004,0)|C = (2004,0), \mathcal{L} = NP]$$

The assumption means that the difference in the evolution of average untreated outcomes among units treated by ozone standards and $\mathcal{L} = P$ and $\mathcal{L} = NP$ for $PM_{2.5}$ in the treated counties for both standards is the same as the difference of the evolution of average untreated outcome among units with ozone standards $\mathcal{L} = P$ and $\mathcal{L} = NP$ for $PM_{2.5}$ in the counties treated for only ozone standard.

The second additional assumption is **non-pathological design**, which means there are at least two groups that started receiving the ozone treatment on the same date and started receiving the $PM_{2.5}$ treatment on different dates. Even though there are sectors that satisfy the non-pathological design, as shown in Table 10, the anticipation assumption contradicts the non-pathological design assumption for this setup.

Table 10: Number of sectors in groups for non-pathological design

Polluter \ County	Ozone	Ozone & $PM_{2.5}$
Ozone	100	21
Ozone & $PM_{2.5}$	348	109
Total	448	130

The table shows the number of sectors in each group. Row (1) denotes the number of sectors that are polluters of ozone in counties regulated for only ozone or both pollutants, while Row (2) shows the number of sectors that are polluters of both pollutants in those counties. This table illustrates the non-pathological design assumption, where groups began receiving ozone treatment on the same date but started receiving $PM_{2.5}$ treatment on different dates, ensuring that there are at least two groups with identical ozone treatment start dates but differing $PM_{2.5}$ treatment initiation dates.

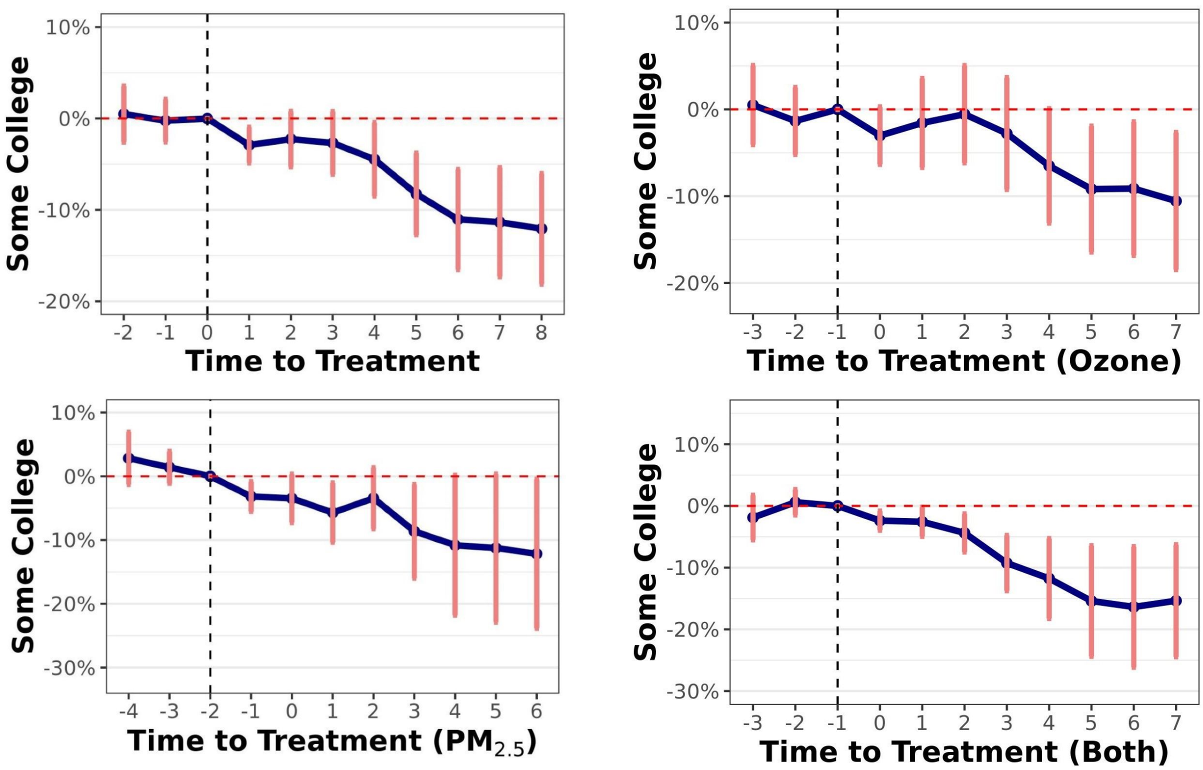
If the additional assumptions, **the restriction on the effect of the ozone standards** and **non-pathological design**, are satisfied, the ATT(g,t) of $PM_{2.5}$ for $g = (2004, 2005)$ as g=(2004,0) as comparison group is the following:

$$\begin{aligned}
ATT(g,t) = & \Bigg[\bigg(\mathrm{E}[Y_t|C = (2004,2005), \mathcal{L} = P] - \mathrm{E}[Y_{g-1}|C = (2004,2005), \mathcal{L} = P]\bigg) \\
& - \bigg(\mathrm{E}[Y_t|C = (2004,2005), \mathcal{L} = NP] - \mathrm{E}[Y_{g-1}|C = (2004,2005), \mathcal{L} = NP]\bigg)\Bigg] \\
& - \Bigg[\bigg(\mathrm{E}[Y_t|C = (2004,0), \mathcal{L} = P] - \mathrm{E}[Y_{g-1}|C = (2004,0), \mathcal{L} = P]\bigg) \\
& - \bigg(\mathrm{E}[Y_t|C = (2004,0), \mathcal{L} = NP] - \mathrm{E}[Y_{g-1}|C = (2004,0), \mathcal{L} = NP]\bigg)\Bigg]
\end{aligned}$$

Appendix B.III

The effect of regulation on some college employment:

Figure 11: Dynamic Effects of Regulation on Some College Employment



Appendix C

Appendix C.I

Workers Value Function Derivation

I begin with equation 19 to rewrite the value function of an unemployed worker k of type i who lives in region r:

$$\begin{aligned} U_r^{i,k}(\lambda) &= b^i - P_r^h + \psi_r + \epsilon_r^k \\ &+ \beta\Big\{\phi_{r,c}^i \mathbb{E}_{\lambda',\epsilon'}\left[E_{r,c}^i(\lambda') + \epsilon_r'^k\right] + \phi_{r,d}^i \mathbb{E}_{\lambda',\epsilon'}\left[E_{r,d}^i(\lambda') + \epsilon_r'^k\right] \\ &+ (1-\phi_{r,c}^i - \phi_{r,d}^i)\mathbb{E}_{\lambda',\epsilon'}\left[\tilde{U}^{i,k}(\lambda')\right]\Big\} \end{aligned}$$

In the first step, I rewrite $\tilde{U}^{i,k}(\lambda')$ for unemployed workers by integrating out the future idiosyncratic shock, exploring Type I EV theory,

$$\begin{aligned} \mathbb{E}_{\lambda',\epsilon'}\left[\tilde{U}^i(\lambda')\right] &= \mathbb{E}_{\lambda',\epsilon'}\left[\max_p U_p^i(\lambda') + \epsilon_p'^k\right] \\ &= \rho\mathbb{E}_{\lambda'} log\left[\sum_{p=1}^N exp(\frac{U_p^i(\lambda')}{\rho})\right] \end{aligned}$$

Using the fact that the expected value of the shock is zero, Gumbell $(-\rho\nu, \rho)$,

$$\begin{aligned} U_r^{i,k}(\lambda) &= b^i - P_r^h + \psi_r + \epsilon_r^k \\ &+ \beta\Big\{\phi_{r,c}^i \mathbb{E}_{\lambda'}\left[E_{r,c}^i(\lambda')\right] + \phi_{r,d}^i \mathbb{E}_{\lambda'}\left[E_{r,d}^i(\lambda')\right] \\ &+ (1-\phi_{r,c}^i - \phi_{r,d}^i)\rho\mathbb{E}_{\lambda'} log\left[\sum_{p=1}^N exp(\frac{U_p^i(\lambda')}{\rho})\right]\Big\} \end{aligned}$$

I add and subtract $\beta(1-\phi_{r,c}^i - \phi_{r,d}^i)\mathbb{E}_{\lambda'}\left[U_r^i(\lambda')\right]$:

$$\begin{aligned} U_r^{i,k}(\lambda) &= b^i - P_r^h + \psi_r + \epsilon_r^k + \beta\mathbb{E}_{\lambda'}\left[U_r^i(\lambda')\right] \\ &+ \beta\phi_{r,c}^i \mathbb{E}_{\lambda'}\left[E_{r,c}^i(\lambda') - U_r^i(\lambda')\right] + \beta\phi_{r,d}^i \mathbb{E}_{\lambda'}\left[E_{r,d}^i(\lambda') - U_r^i(\lambda')\right] \\ &+ \beta(1-\phi_{r,c}^i - \phi_{r,d}^i)\rho\mathbb{E}_{\lambda'} log\left[\sum_{p=1}^N exp(\frac{U_p^i(\lambda')}{\rho})\right] - \beta(1-\phi_{r,c}^i - \phi_{r,d}^i)\mathbb{E}_{\lambda'}\left[U_r^i(\lambda')\right] \end{aligned} \tag{30}$$

Focusing on the last term of the previous equation:

$$\beta(1-\phi_{r,c}^i - \phi_{r,d}^i)\rho\mathbb{E}_{\lambda'} log\left[\sum_{p=1}^N exp(\frac{U_p^i(\lambda')}{\rho})\right] - \beta(1-\phi_{r,c}^i - \phi_{r,d}^i)\mathbb{E}_{\lambda'}\left[U_r^i(\lambda')\right]$$

And making the following substitution:

$$-\beta(1-\phi^i_{r,c}-\phi^i_{r,d})\mathbb{E}_{\lambda'}\left[U^i_r(\lambda')\right] = -\beta(1-\phi^i_{r,c}-\phi^i_{r,d})\rho\mathbb{E}_{\lambda'}\left[log\left[exp(\frac{U^i_r(\lambda')}{\rho})\right]\right]$$

yields:

$$\beta(1-\phi^i_{r,c}-\phi^i_{r,d})\rho\mathbb{E}_{\lambda'}\left[log\left[\sum_{p=1}^{N} exp(\frac{U^i_p(\lambda')}{\rho})\right] - log\left[exp(\frac{U^i_r(\lambda')}{\rho})\right]\right]$$

Next, using properties of logarithms:

$$\beta(1-\phi^i_{r,c}-\phi^i_{r,d})\rho\mathbb{E}_{\lambda'}\left[log\left[\frac{\sum_{p=1}^{N} exp(\frac{U^i_p(\lambda')}{\rho})}{exp(\frac{U^i_r(\lambda')}{\rho})}\right]\right]$$

Further, using properties of the exponential function:

$$\beta(1-\phi^i_{r,c}-\phi^i_{r,d})\rho\mathbb{E}_{\lambda'}\left[log\left[\sum_{p=1}^{N} exp(\frac{U^i_p(\lambda')-U^i_r(\lambda')}{\rho})\right]\right]$$

Finally, by using the probability of choosing region r, δ^i_{r},:

$$\beta(1-\phi^i_{r,c}-\phi^i_{r,d})\rho\mathbb{E}_{\lambda'}log\left[1+\sum_{p\neq r}^{N} exp(\frac{U^i_p(\lambda')-U^i_r(\lambda')}{\rho})\right] =$$
$$\beta(1-\phi^i_{r,c}-\phi^i_{r,d})\rho\mathbb{E}_{\lambda'}log(1/\delta^i_r)$$

which yields the following result:

$$\begin{aligned} U^{i,k}_r(\lambda) &= b^i - P^h_r + \psi_r + \epsilon^k_r + \beta\mathbb{E}_{\lambda'}\left[U^i_r(\lambda')\right] \\ &+ \beta\phi^i_{r,c}\mathbb{E}_{\lambda'}\left[E^i_{r,c}(\lambda') - U^i_r(\lambda')\right] + \beta\phi^i_{r,d}\mathbb{E}_{\lambda'}\left[E^i_{r,d}(\lambda') - U^i_r(\lambda')\right] \\ &+ \beta(1-\phi^i_{r,c}-\phi^i_{r,d})\rho\mathbb{E}_{\lambda'}log(1/\delta^i_r) \end{aligned} \tag{31}$$

To rewrite the value function for employed workers, I followed similar steps by adding and subtracting $\beta(1-\pi^i_{r,j})\mathbb{E}_{\lambda'}\left[U^i_r\right]$

$$\begin{aligned} E^{i,k}_{r,j}(\lambda) &= w^i_{r,j} - P^h_r + \psi_r + \epsilon^k_r + \beta\mathbb{E}_{\lambda'}\left[U^i_r(\lambda')\right] + \beta(1-\pi^i_{r,j})\mathbb{E}_{\lambda'}\left[E^i_{r,j}(\lambda') - U^i_r(\lambda')\right] \\ &+ \beta\pi^i_{r,j}\rho\mathbb{E}_{\lambda'}(log(1/\delta^i_r)) \end{aligned}$$

Appendix C.II

Total Surplus and Wage Equation Derivation

In equilibrium, the free-entry condition implies that $V^i_{r,j}(\lambda) = 0$. So, a firm's surplus is:

$$J^i_{r,j} = p_j A_r z^i_j - w^i_{r,j} + \beta(1 - \pi^i_{r,j}) J^i_{r,j}$$

and a worker's surplus is:

$$\begin{aligned} E^i_{r,j} - U^i_r = {} & w^i_{r,j} - b^i + \beta(1 - \pi^i_{r,j}) \left[E^i_{r,j} - U^i_r\right] - \beta\phi^i_{r,c} \left[E^i_{r,c} - U^i_r\right] \\ & - \beta\phi^i_{r,d} \left[E^i_{r,d} - U^i_r\right] + \beta(\pi^i_{r,j} - (1 - \phi^i_{c,r} - \phi^i_{d,r}))\rho log(1/\delta_r) \end{aligned}$$

Total surplus is $S^i_{r,j} = J^i_{r,j} + E^i_{r,j} - U^i_r$ and $J^i_{r,j} = (1 - \eta)S^i_{r,j}$ and $E^i_{r,j} - U^i_r = \eta S^i_{r,j}$.
Hence, the total surplus can be written as:

$$\begin{aligned} S^i_{r,j} &= p_j y^i_{r,j} - w^i_{r,j} + \beta(1 - \pi^i_{r,j})(1 - \eta)S^i_{r,j} + w^i_{r,j} - b^i + \beta(1 - \pi^i_{r,j})\eta S^i_{r,j} \\ &\quad - \beta\phi^i_{r,c}\eta S^i_{r,c} - \beta\phi^i_{r,d}\eta S^i_{r,d} + \beta(\pi^i_{r,j} - (1 - \phi^i_{c,r} - \phi^i_{d,r}))\rho log(1/\delta_r) \\ &= p_j y^i_{r,j} - b^i + \beta(1 - \pi^i_{r,j})S^i_{r,j} - \beta\phi^i_{r,c}\eta S^i_{r,c} - \beta\phi^i_{r,d}\eta S^i_{r,d} + \beta(\pi^i_{r,j} - (1 - \phi^i_{c,r} - \phi^i_{d,r}))\rho log(1/\delta_r) \end{aligned}$$

The surplus functions for type i in region r:

$$\begin{aligned} S^i_{r,c} &= p_c A_r z^i_c - b^i + \beta(1 - \pi^i_{r,c} - \phi^i_{r,c}\eta)S^i_{r,c} - \beta\phi^i_{r,d}\eta S^i_{r,d} + \beta(\pi^i_{r,c} - (1 - \phi^i_{c,r} - \phi^i_{d,r}))\rho log(1/\delta_r) \\ S^i_{r,d} &= p_d A_r z^i_d - b^i + \beta(1 - \pi^i_{r,d} - \phi^i_{r,d}\eta)S^i_{r,d} - \beta\phi^i_{r,c}\eta S^i_{r,c} + \beta(\pi^i_{r,d} - (1 - \phi^i_{c,r} - \phi^i_{d,r}))\rho log(1/\delta_r) \end{aligned} \tag{32}$$

To derive the wage equation of type i in sector j and region r, I use the fact that $\eta J^i_{r,j} = (1 - \eta)(E^i_{r,j} - U^i_r)$:

$$\begin{aligned} &\eta p_j y^i_{r,j} - \eta w^i_{r,j} + \eta\beta(1 - \pi^i_{r,j})J^i_{r,j} = (1 - \eta)w^i_{r,j} - (1 - \eta)b^i + (1 - \eta)\beta(1 - \pi^i_{r,j}) \left[E^i_{r,j} - U^i_r\right] \\ &- (1 - \eta)\beta\phi^i_{r,c} \left[E^i_{r,c} - U^i_r\right] - (1 - \eta)\beta\phi^i_{r,d} \left[E^i_{r,d} - U^i_r\right] + (1 - \eta)\beta(\pi^i_{r,j} - (1 - \phi^i_{c,r} - \phi^i_{d,r}))\rho log(1/\delta_r) \end{aligned}$$

This gives us:

$$\begin{aligned} w^i_{r,j} = {} & \eta p_j y^i_{r,j} + (1 - \eta)b^i + \beta\phi^i_{r,c}\eta J^i_{r,c} + \beta\phi^i_{r,d}\eta J^i_{r,d} \\ & - (1 - \eta)\beta(\pi^i_{r,j} - (1 - \phi^i_{c,r} - \phi^i_{d,r}))\rho log(1/\delta_r) \end{aligned}$$

In equilibrium $J^i_{r,j} = \frac{\kappa^i_j}{\beta q(\theta^i_{r,j})}$ and $\phi^i_{r,c} = \theta^i_{r,j} q(\theta^i_{r,j})$. Hence, I can rewrite the wage equation as:

$$\begin{aligned} w^i_{r,j} = {} & \eta p_j y^i_{r,j} + (1 - \eta)b^i + \eta\theta^i_{r,c}\kappa^i_c + \eta\theta^i_{r,d}\kappa^i_d \\ & - \beta(1 - \eta)(\pi^i_{r,j} - (1 - \phi^i_{c,r} - \phi^i_{d,r}))\rho log(1/\delta_r) \end{aligned}$$

The free-entry conditions for sectors for type i in region r also gives us:

$$\begin{aligned} S^i_{r,c} &= \frac{\kappa_c}{\beta(1-\eta)q(\theta^i_{r,c})} \\ S^i_{r,d} &= \frac{\kappa_d}{\beta(1-\eta)q(\theta^i_{r,d})} \end{aligned} \tag{33}$$

Market Clearing Conditions:

$$Y_c = \frac{\Omega C}{p_c^{1-\chi}} = \sum_{r=\{1,\ldots,N\}} n^l_{r,c} A_r z^l_c + n^h_{r,c} A_r z^h_c$$

$$Y_d = \frac{\Omega C}{p_d^{1-\chi}} = \sum_{r=\{1,\ldots,N\}} n^l_{r,d} A_r z^l_d + n^h_{r,d} A_r z^h_d$$

Appendix C.III

Worker Flows

The flow of the number of unemployed workers in the region r is the following:

$$\begin{aligned} u_r'^i &= Pr(\text{staying r})[(1-\phi^i_{c,r}-\phi^i_{d,r})u^i_r + \sum_j \pi^i_{r,j}n^i_{r,j}] \\ &+ \sum_{p\neq r} Pr(\text{moving from p to r})[(1-\phi^i_{c,p}-\phi^i_{d,p})u^i_p + \sum_j \pi^i_{p,j}n^i_{p,j}] \end{aligned} \tag{34}$$

where $n^i_{r,j}$ is the employed workers for type i in sector j, in region r.

In equilibrium, worker inflows should be equal to outflows across regions, which gives us the following:

$$\begin{aligned} \sum_{p\neq r} Pr(\text{moving from p to r})[(1-\phi^i_{c,p}-\phi^i_{d,p})u^i_p + \sum_j \pi^i_{p,j}n^i_{p,j}] = \\ Pr(\text{leaving r})[(1-\phi^i_{c,r}-\phi^i_{d,r})u^i_r + \sum_j \pi^i_{r,j}n^i_{r,j}] \end{aligned} \tag{35}$$

Substituting the RHS of the equation 35 into equation 34 and using 1 - Pr(staying r) = Pr(leaving r) yields:

$$u_r'^i = (1-\phi^i_{c,r}-\phi^i_{d,r})u^i_r + \sum_j \pi^i_{r,j}n^i_{r,j} \tag{36}$$

Furthermore, the measure of employed workers of type i in region r - sector j:

$$n'^i_{r,j} = (1-\pi^i_{r,j})n^i_{r,j} + \phi^i_{r,j}u^i_r \tag{37}$$

which implies $\pi^i_{r,j}n^i_{r,j} = \phi^i_{r,j}u^i_r$ in equilibrium.

Appendix D

Appendix D.I

North Carolina

Figure 12: Number of Nonattainment Counties in North Carolina over Years

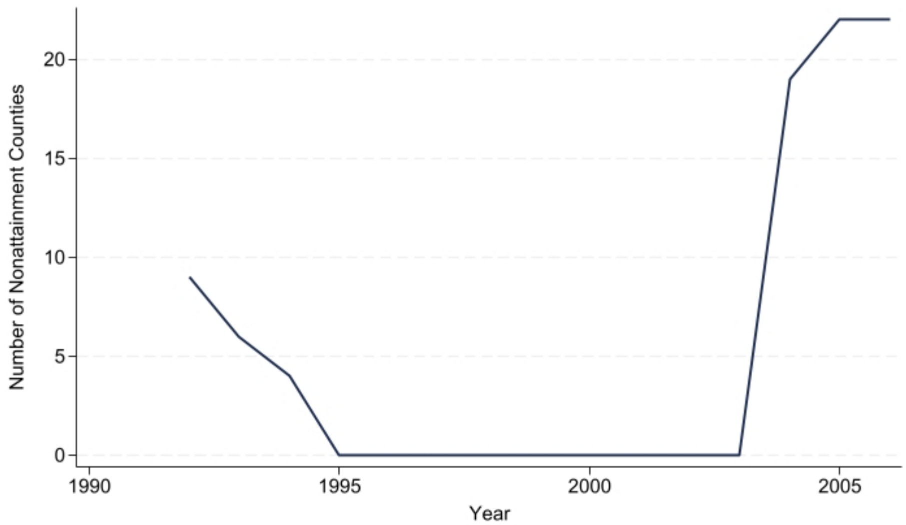
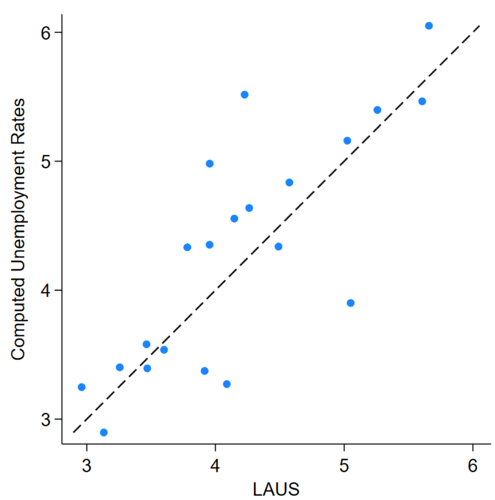


Figure displays the number of nonattainment counties in North Carolina over time. In 2004, 19 counties were designated as nonattainment for ozone standards, while three were designated as nonattainment for $PM_{2.5}$ standards in 2005.

Figure 13: Computed Unemployment Rate and LAUS Comparision



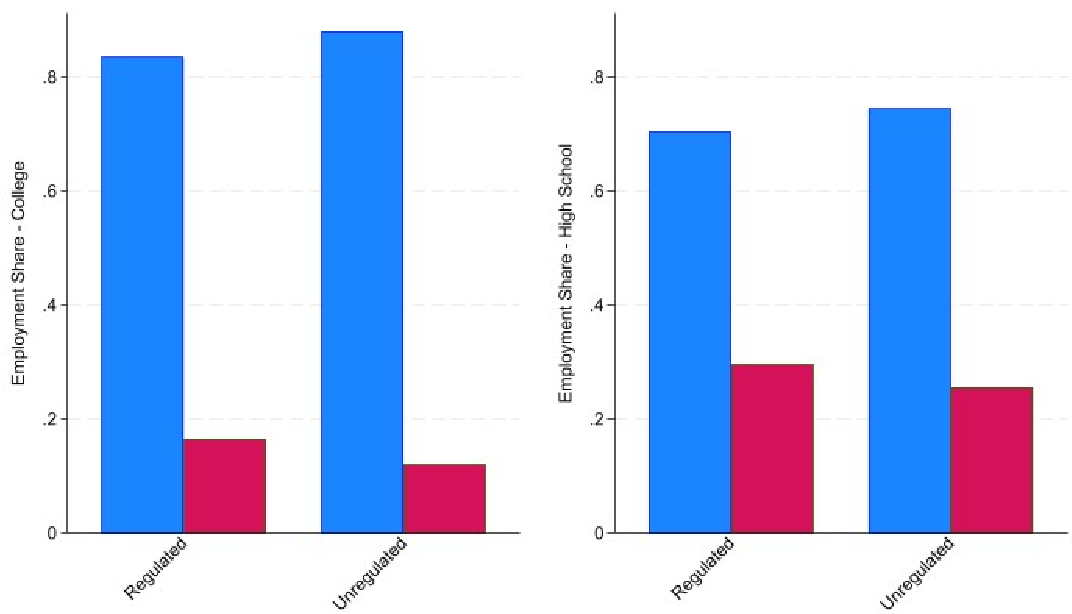
The figure presents the comparison of unemployment rates of commuting zones in North Carolina, as calculated using the methodology outlined in Appendix A.III, to unemployment rates obtained from Local Area Statistical data.

Table 11: Share of Plants with Permits across Sectors in North Carolina

Sector	**Description**	**Share of plants for ozone permits**	**Share of plants for PM2.5 permits**
11	Agriculture, Forestry, Fishing and Hunting	0.93	1.81
21	Mining, Quarrying, and Oil and Gas Extraction	1.74	5.91
22	Utilities	6.99	3.30
23	Construction	0.25	0.27
31-33	Manufacturing	74.05	77.3
42	Wholesale Trade	2.65	2.79
44-45	Retail Trade	2.58	0.2
48-49	Transportation and Warehousing	1.33	0.65
51	Information	1.11	0.23
52	Finance and Insurance	0.15	0.06
53	Real Estate and Rental and Leasing	0.03	0.04
54	Professional, Scientific, and Technical Services	0.71	0.43
55	Management of Companies and Enterprises	0	0
56	Administrative and Support and Waste Management and Remediation Services	1.84	1.50
61	Educational Services	0.66	0.94
62	Health Care and Social Assistance	1.94	2.03
71	Arts, Entertainment, and Recreation	0.08	0.08
72	Accommodation and Food Services	0.03	0.04
81	Other Services (except Public Administration)	2.19	1.58
92	Public Administration (not covered in economic census)	0.86	0.86
Total number of permits issued		3,965	5,127

Note: Table shows the share of plants with permits across sectors in North Carolina. Source: The EPA's Air Facility Subsystem (AFS).

Figure 14: Sectoral Employment Shares by Education and CZ Regulatory Status



Note: Figure presents the average employment shares across sectors, segmented by education level and the regulatory status of commuting zones in North Carolina. Blue bars represent the employment share in clean sectors, while red bars represent the employment share in dirty sectors.

Rental Index Construction and Housing Market Parameters

I construct a rental index for each commuting zone in my sample to enable a more accurate comparison of housing prices across different CZs, following the approach in Morehouse (2021). After linking households from the 2000 ACS 5-year sample to their corresponding commuting zones, I estimate a regression of individual gross log rent on commuting zone fixed effects and housing characteristics, consistent with standard practices in the literature. The housing characteristics included in the regression are the number of bedrooms and rooms, the ratio of household members to rooms, and the total number of housing units in the structure containing the household.

$$\log(R_i) = \beta_{\mathrm{CZ}(i)} + \beta_2 \mathrm{Rooms}_i + \beta_3 \mathrm{Units}_i + \beta_4 \mathrm{Bedrooms}_i + \beta_5 \left(\frac{\mathrm{members}_i}{\mathrm{rooms}_i} \right) + \epsilon_i$$

Next, I compute the average of these housing characteristics across all commuting zones and hold them constant. Using the estimated coefficients for commuting zone fixed effects, I construct predicted values for the rental index. The reference commuting zone used as a baseline is the one with the median unemployment rate.

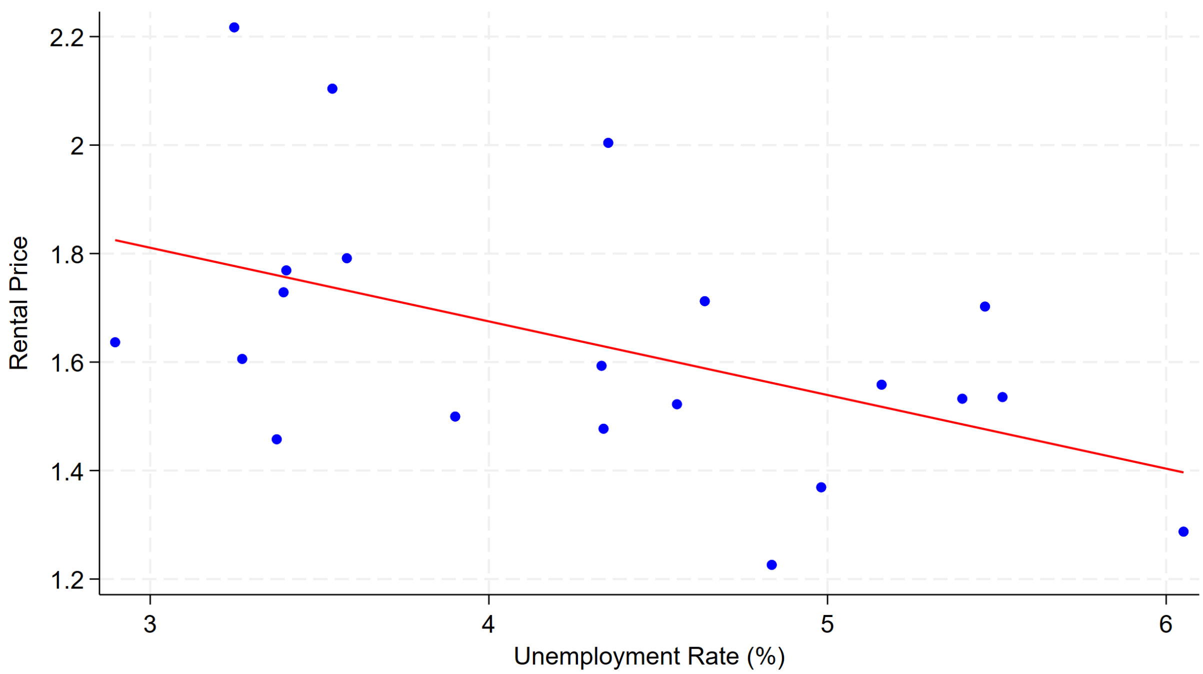
The inverse housing supply function is given by $P_r^h = \bar{H}_r \lambda_r^{\sigma_r}$, where $\bar{H}_r$ represents location-specific intercepts, $\lambda_r$denotes the population in the location, and σ_r corresponds to the location-specific housing elasticity.

The housing elasticities (σ_r) are taken directly from Saiz (2010) whenever possible. Saiz provides estimates for metropolitan statistical areas (MSAs), which I use as proxies for the corresponding commuting zones. I select the closest MSA elasticity from Saiz (2010) for commuting zones that consist only of micropolitan areas or small counties. Since the elasticities in Saiz's study are based on land restrictions within a 50-kilometer radius, I limit the choice of MSAs to those located within this distance from the counties in the commuting zone.

To finalize the housing market parameters, I use the inverse housing supply equation to calibrate the location-specific constants by incorporating the predicted rental index, housing elasticities, and the labor force distribution within each commuting zone, $\bar{H}_r = \frac{P_r^h}{\lambda_r^{\sigma_r}}$.

This approach allows for a robust comparison of rents across commuting zones, considering regional differences in housing supply elasticity and population. Figure 15 plots the predicted rental price index against unemployment rates across commuting zones.

Figure 15: Predicted Rental Price Index and Unemployment Rate Across Commuting Zones



Note: Figure plots the predicted rental price index against unemployment rates across commuting zones.

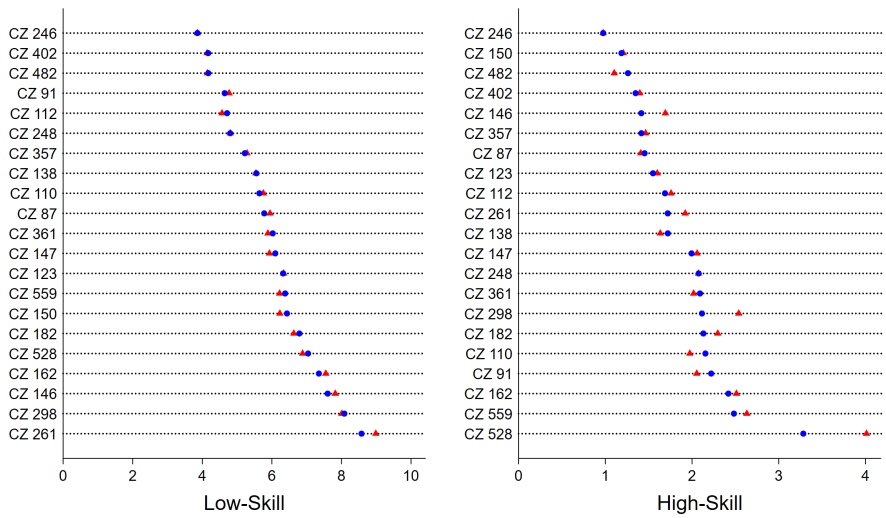
Table 12: Model Parameters in Commuting Zones

Commuting Zones	Housing Parameters		Productivity				Separation Rates				Base Level Local Amenities	
	σ_r	$\bar{H}_r$	z_c^l	z_d^l	z_c^h	z_d^h	π_c^l	π_d^l	π_c^h	π_d^h	ψ_l^B	ψ_h^B
87	2.11	0.0046	1.242	2.649	2.845	4.789	0.054	0.092	0.014	0.011	1.176	0.257
91	1.55	0.1772	1.206	2.256	2.203	3.646	0.047	0.053	0.021	0.017	0.763	0.930
110	1.83	0.2631	1.304	2.939	2.416	4.975	0.050	0.114	0.018	0.031	0.832	0.577
112	3.10	0.0068	1.134	2.096	2.340	4.329	0.045	0.049	0.017	0.017	0.838	0.527
123	1.55	1.6160	1.084	1.796	1.693	2.326	0.062	0.075	0.015	0.024	0.771	1.490
138	3.09	0.0002	1.364	2.016	2.785	3.388	0.062	0.039	0.017	0.004	1.076	0.436
146	3.08	0.0889	1.136	1.987	2.197	3.191	0.092	0.054	0.018	0.009	0.751	0.701
147	0.82	1.3962	1.000	1.932	2.020	3.796	0.054	0.120	0.018	0.052	1.000	1.000
150	3.10	3.7426	1.018	1.533	1.619	2.343	0.095	0.026	0.014	0.005	0.628	1.297
162	2.71	0.0197	0.998	1.953	1.797	2.989	0.078	0.075	0.025	0.019	1.088	1.576
182	1.96	0.2540	1.009	1.657	1.758	2.930	0.065	0.084	0.021	0.036	1.186	1.639
246	2.41	0.0360	1.129	1.608	1.861	2.952	0.069	0.013	0.012	0.004	0.908	1.304
248	3.10	0.0006	1.199	1.818	2.221	3.453	0.060	0.026	0.022	0.012	0.970	0.990
261	3.08	0.4612	0.867	1.569	1.634	2.564	0.098	0.077	0.019	0.016	0.938	1.373
298	1.96	0.1496	1.077	2.071	2.069	3.587	0.083	0.079	0.025	0.024	0.854	0.935
357	1.02	2.3733	1.018	1.335	1.671	2.153	0.059	0.033	0.015	0.011	0.923	1.532
361	2.71	0.0202	1.118	2.033	2.129	3.324	0.069	0.044	0.024	0.008	0.672	0.826
402	1.45	6.6126	1.021	1.440	1.561	2.048	0.054	0.020	0.015	0.008	0.947	1.807
482	2.41	0.2951	1.138	1.401	1.931	2.398	0.052	0.015	0.011	0.004	0.728	1.074
528	2.71	0.4617	1.076	1.296	1.922	2.292	0.091	0.025	0.043	0.009	0.989	1.335
559	3.12	0.0955	1.051	1.588	1.825	2.779	0.071	0.040	0.026	0.019	0.772	1.206

Note: This table presents model parameters across various commuting zones. Columns are organized by parameter type, including housing parameters, productivity levels, separation rates, and base-level local amenities. The housing parameters consist of the elasticity of substitution between land and housing, σ_r, and the baseline housing supply, $\bar{H}_r$. Productivity levels are represented for both clean (z_c) and dirty sectors (z_d) by skill level (low-skill l and high-skill h). Separation rates, π, are similarly divided by clean and dirty sectors and skill levels. Finally, base-level local amenities for low-skill (ψ_l^B) and high-skill workers (ψ_h^B) capture the inherent desirability of each commuting zone for workers of different skill levels.

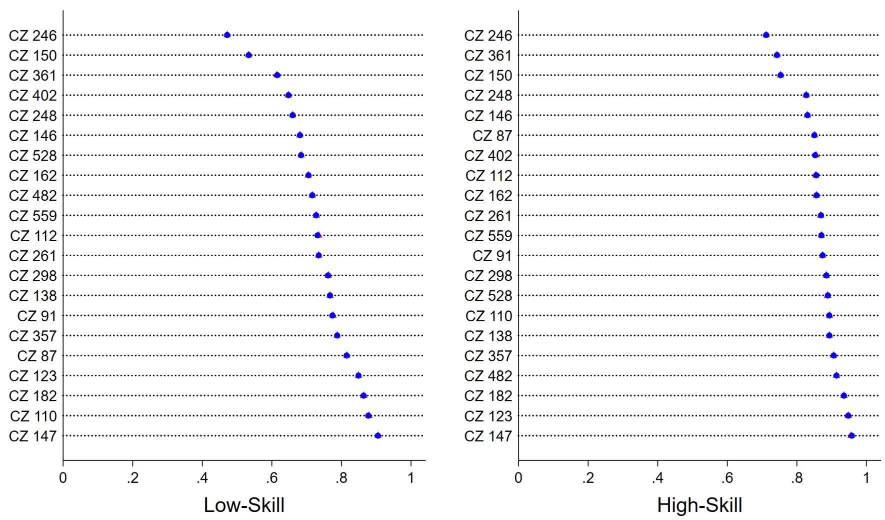
Model Fit - Targeted Moments

Figure 16: Model vs. Data - Unemployment Rate



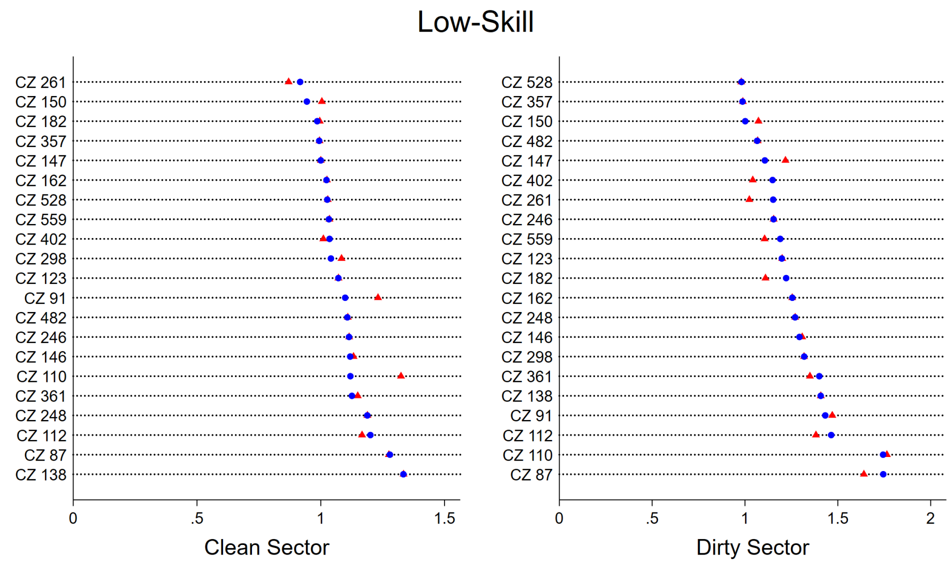
Note: This figure shows the model fit by comparing the targeted unemployment rates with the model's predicted results for both low- and high-skill workers. The comparison illustrates how closely the model aligns with the actual unemployment rates for each skill group.

Figure 17: Model vs. Data -Share of Clean Sector Employment

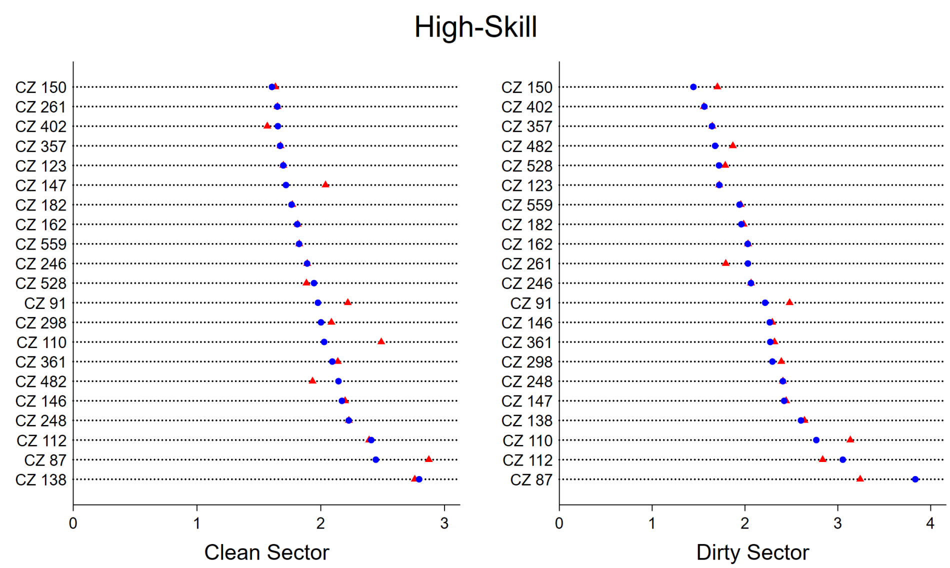


Note: This figure compares the model's predicted share of clean sector employment with the actual data. The comparison assesses the model's accuracy in capturing the distribution of employment within clean sectors, providing insight into how well the model replicates observed employment patterns across sectors.

Figure 18: Model vs. Data - Relative Wages

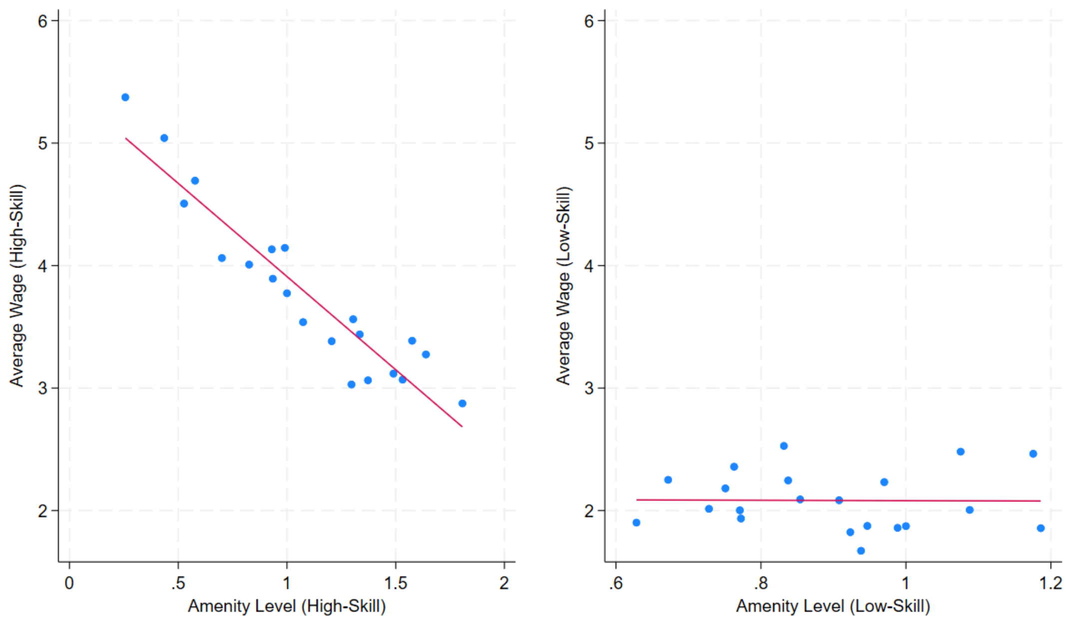


Note: This figure compares the model's predicted relative wages for low-skill workers with the actual data. This comparison evaluates the model's ability to replicate wage patterns for low-skill workers.



Note: This figure compares the model's predicted relative wages for high-skill workers with the actual data. This comparison evaluates the model's ability to replicate wage patterns for high-skill workers.

Figure 19: Amenities vs. Average Wages



Note: This figure illustrates the model's results for amenity levels and average wages for high- and low-skill workers. While there is a negative relationship between base-level amenity values and average wages for high-skill workers, no significant relationship is observed for low-skill workers.