The Geography of Environmental Regulation*

Welfare and Distributional Impacts of the Clean Air Act

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Abstract

This paper introduces an integrated spatial general equilibrium air quality assessment model to quantify the impact of the National Ambient Air Quality Standards (NAAQS) under the Clean Air Act. Using a quasi-experiment in regulatory changes, we use the model structure to guide estimation of the direct effects of nonattainment on emissions and productivity. We use these estimates in the model to simulate the economy-wide impacts of NAAQS nonattainment designations in the 1990s on emissions and productivity. The NAAQS increases welfare of 0.49 percent (or $19.3 billion per year); improved amenities account for a substantial portion of the overall effect, while real income losses are modest and concentrated among workers in polluting sectors. Approximately one fifth of the total benefits accrue to workers in counties that are in attainment. The results highlight the importance of accounting for the spatial linkages when quantifying the effects of environmental regulation.

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1 Introduction

Over the last several decades, governments around the world have enacted regulations intended to improve environmental quality. Environmental protections directly benefit individuals through improved health, recreation, and other channels, but more stringent regulation of polluting activities imposes substantial costs on producers. One key feature of air pollutants is that they are spatially local, causing more damage near the source of emission and less further away. This "physical geography" along with standard frictions in economic geography mean that the benefits and costs of environmental policy will be distributed heterogeneously across space, sectors, and households. Accounting for these factors and how the economy reallocates in response to changes in regulation is critical for understanding the efficiency and distributional implications of environmental policy.

The goal of this paper is to better understand the welfare and distributional implications of the National Ambient Air Quality Standards (NAAQS), the primary piece of air quality regulation in the Clean Air Act (CAA). We tackle this goal in two steps. First, we develop a general theoretical framework that can be used to assess economic impacts of any spatial intervention that affects productivity, amenities, or both. We build a multisector economic geography model in the spirit of Eaton and Kortum (2002). Our economic model is linked to a benchmark integrated assessment model for air pollution, which enables us to map the spatial distribution of air emissions into ambient concentrations of fine particulate matter and local amenities (Muller and Mendelsohn, 2009; Muller, Mendelsohn and Nordhaus, 2011; Tschofen, Azevedo and Muller, 2019). We apply the model to US counties and allow local productivity and emissions to be determined by the effects of the NAAQS.

Second, we use the model to quantify the impact of the NAAQS on productivity, emissions, and amenities. We use the structure of the model to guide estimation — rather than taking a reduced-form approach — so that our estimates of the effect of regulation explicitly incorporate the potential role of spillovers across treatment and control units through general equilibrium channels. We then use the empirical results together with the equilibrium conditions of the model to compute counterfactual aggregate welfare and evaluate the distributional effects of the NAAQS in the presence of trade, migration, and sectoral reallocation.

A growing empirical literature has identified large effects of environmental regulation on labor market, firm, health, and housing outcomes (Shapiro, 2021). Recent work exploiting quasi-experimental research designs has studied on the economic and environmental impacts of the Clean Air Act (CAA) (Currie and Walker, 2019) — the primary set of federal air quality regulations in the United States. This research has largely focused on the individual components of costs and benefits. A unified, quantitative equilibrium approach, like the one we undertake, is required to understand the aggregate welfare implications and the distributional consequences of the Clean Air Act or similar environmental regulations.

We identify the direct effects on emissions and productivity in spatial equilibrium by using quasi-experimental variation in county-level nonattainment status caused by changes to the NAAQS under the 1990 CAA amendments. If ambient concentrations of one of a set of "criteria" pollutants exceeds the NAAQS threshold in a county, that county is designated as in *nonattainment* (versus in *attainment*). The 1990 CAA amendments increased regulatory scrutiny and costs to polluting firms by adding a new class of pollutants to the NAAQS — particulate matter smaller than 10 micrometers in diameter (PM_{10}) — and scheduling a formal re-evaluation of the current set of nonattainment statuses. This lead to the largest increase in nonattainment designations since 1978 (Walker, 2013). Reduced form evidence has shown that nonattainment designation makes it more costly for polluting firms to enter, induces exit of incumbent firms, and has negative effects on the polluting industry's workforce, output, and productivity (Henderson, 1996; Becker and Henderson, 2000; Greenstone, 2002; Walker, 2013).

We estimate the impact of nonattainment designations on the implicit marginal cost (i.e. shadow price) that firms face for emissions by comparing within-county emissions before and after the new nonattainment designations, while conditioning on the wage bill.[1] We find the price of emissions of five particulate pre-cursors increases by an average of 35 percent, but with significant heterogeneity. This estimate isolates what is commonly called the *technique effect* — the change in emissions intensity of output — because we are estimating the effect of nonattainment on emissions in the polluting industry, conditional on the size of the polluting industry (Antweiler et al., 2001; Copeland and Taylor, 2013; Cherniwchan et al., 2017).

We then estimate the effect of nonattainment status on productivity by comparing changes in income in polluting versus non-polluting industries in the same county before and after a new nonattainment designation caused by the 1990 CAA amendments. Effects on productivity will constitute a combination of the traditional *scale* and *composition* effects because changes in productivity of the polluting industry will affect the size of the total economy, and the share of the polluting industry in the economy. We find a relative decrease in productivity of 5 percent. One feature of this result highlights the importance of accounting for general equilibrium spillovers for the purposes of policy evaluation. Directly controlling for a transformation of real wages allows us to isolate the direct impact of nonattainment status on productivity since omitting controls for spatial and sectoral linkages introduces

[1] We show that controlling for the wage bill is theoretically important to separately identify the effect of nonattainment on the implicit price of emissions versus a change in productivity. In practice, this adjustment does not affect the estimated coefficients.

bias. We document differences across specifications that include or exclude these controls, which suggests that accounting for these confounds is crucial and may be an important consideration in other settings.

Using these estimates, we quantify the aggregate and distributional impacts with a spatial equilibrium model. We conduct counterfactuals where we simulate 1997 equilibrium outcomes as if counties never went into nonattainment.[2] Using the hat algebra approach in Dekle, Eaton and Kortum (2008) we compute changes in welfare, sectoral employment, and population outcomes under the actual nonattainment designations with a counterfactual scenario in which no county is in nonattainment. The results imply a 0.52 percent increase in welfare from improved amenities through lower fine particulate concentrations, and a 0.03 percent decrease from lower real wages driven by lower productivity. Overall, welfare increases by 0.49 percent or $19.3 billion per year. In present value terms at a three percent discount rate, total benefits are over half a trillion dollars.[3]

We next decompose these effects across sectors and regions. We find that although there are a large number of counties that are made worse off from nonattainment, in the aggregate, workers in both the polluting and nonpolluting sectors are better off, and workers in both attainment and nonattainment counties are also better off. The main polluting sector in our setting, manufacturing, has workers experiencing real wage losses of 0.17 percent, but their welfare gains from amenities are three times larger in magnitude. Workers in nonpolluting (nonmanufacturing) sectors experience larger welfare gains since the impact on their real wages is effectively zero. The per-capita welfare gains are also highly unequal across space and accrue mostly to high population, urban counties.

Finally, we quantify the economic and physical mechanisms underlying the margins of adjustment. We find that the effect of nonattainment on the implicit price of emissions accounts for more than 100 percent of the welfare gains. If nonattainment only affected firm productivity and did not directly affect the relative price of emissions welfare would decline by 0.11 percent. In response to nonattainment's effects on productivity and the price of emissions, labor will reallocate across space and industries. Reallocation has a positive effect on real wages as standard economic theory would suggest, but in our setting it also has a negative effect from reallocating emissions into higher marginal damage areas. Both of these effects are small, but the negative effect dominates so that labor reallocation reduces aggregate welfare. Changes in productivity and implicit emissions prices also lead

[2]We use 1997 as the benchmark year since it is just prior to the update of the ozone NAAQS and the introduction of $PM_{2.5}$ as a new NAAQS criteria pollutant.

[3]The actual net benefits are likely even larger. Our quantitative model only accounts for damages from formation of $PM_{2.5}$, and our reduced form amenity regression in the appendix suggests that the amenity benefits may be over three times larger.

to changes in emissions and amenities in all counties. Our quantitative results show that about 15 percent of the amenities gains occur in attainment counties, and about half of the benefits from nonattainment designations are from avoiding pollution that would have crossed county borders. This highlights the role of accounting for physical processes when evaluating the benefits of environmental policy.

This paper is related to a large empirical literature on the impact of environmental regulation and, more specifically, the Clean Air Act. One strand of this literature estimates the effect of the NAAQS and nonattainment designations. The NAAQS have well-documented air quality and health benefits (Chay et al., 2003; Auffhammer et al., 2009; Isen et al., 2017), and these benefits are capitalized into housing values and rents (Chay and Greenstone, 2005; Grainger, 2012; Bento et al., 2015). However, these benefits come at a cost. Several papers have found negative effects on firms through reduced productivity and reduced competitiveness, and negative effects on workers through lower wages, and increased rates of nonemployment and job transitions (Becker and Henderson, 2000; Greenstone, 2002; Greenstone et al., 2012; Walker, 2013).[4]

Another strand of the environmental regulation literature emphasizes the role of general equilibrium responses. This literature has studied the efficiency (Bovenberg and Goulder, 1996; Goulder et al., 1999; Bento et al., 2009; Goulder et al., 2016) and incidence (Fullerton and Heutel, 2007, 2010, 2011; Hafstead and Williams III, 2018) of different types of policies, mostly in stylized settings. Most closely related to our paper is work by Shapiro and Walker (2018) that uses a quantitative trade model to show that environmental regulation has been the primary cause of the remarkable decline in US manufacturing emissions.

We unify these strands of the literature by performing the first analysis of the CAA in the context of a quantitative spatial model. Our approach is novel in several ways. First, we estimate impacts the price of emissions and productivity in a way that consistently accounts for spatial linkages due to trade and labor mobility. Second, we take the model to the data using these estimates, novel data on cross-county shipping costs to accurately capture trade frictions, and migration data as a sufficient statistic for unobserved mobility costs. Capturing trade and mobility costs is necessary for estimating the direct effects and quantifying spatial and sectoral heterogeneity using our model. In the absence of county-level data on trade flows within the United States, the only way to evaluate the NAAQS is to use a direct measure of trade costs. For this, we draw on recent work by Jaworski and Kitchens (2021) to quantify trade costs via the US highway network.

[4]There is also a related hedonic literature valuing air quality and temperature using migration and housing prices (Bayer et al., 2009; Bajari et al., 2012; Kuminoff et al., 2013; Albouy et al., 2016; Chen et al., 2017). In the appendix we use a similar approach to validate the structure and results of our quantitative model using cross-county migration flows.

Our paper sheds new light on the impacts of the Clean Air Act. We show that in annualized terms, billions of dollars of benefits from improved amenities, and hundreds of millions of dollars of benefits from improved real wages, actually accrue to counties that never enter nonattainment. The amenity benefits are driven by cross-county spillovers of pollution reductions while the income benefits are driven mostly by reallocation of labor and decreased competition facing firms in attainment counties.

These physical and economic spillovers reveal several important facts. First, and most importantly, the welfare benefits of the NAAQS are larger than previously estimated. Second, the empirical literature estimating the value of improved air quality by comparing nonattainment and attainment counties has been biased toward zero due to violations of the Stable Unit Treatment Value Assumption through economic and physical channels. Attainment counties account for about one fifth of the total welfare gains which suggests the magnitudes are substantial. Third, labor market reallocation has highly heterogeneous effects. Reallocation reduces welfare in some major population centers by up to 2 percent — four times the average welfare gain from nonattainment — because of pecuniary and real externalities. The largest gains from reallocation are only 0.25 percent.

Finally, our paper is related to recent research using economic geography models to examine the economic impacts of environmental change (Dingel, Meng and Hsiang, 2018; Aldeco, Barrage and Turner, 2019; Hanlon, 2020; Balboni, 2021; Heblich, Trew and Zylberberg, 2021; Cruz and Rossi-Hansberg, 2021; Nath, 2021; Rudik, Lyn, Tan and Ortiz-Bobea, 2021).[5] We add to this literature by studying environmental regulation and its impact on the environment by integrating standard features of economic geography models with a workhorse air pollution integrated assessment model.

The remainder of this paper is organized as follows. The next section provide an overview of the Clean Air Act with a focus on the 1990 amendments and the institutional details that inform our methodological choices. Section 3 provides an overview of the theoretical framework. Section 4 discusses the data. Section 5 describes our empirical strategy and the results for the direct effects of the Clean Air Act on productivity and emissions. Section 6 presents the counterfactual results. Section 7 concludes.

[5]In earlier work on geography and the environment, Copeland and Taylor (1999) show that trade can mitigate pollutant damages by spatially separating polluting industries and sensitive locations. Early equilibrium analyses of the Clean Air Act in the 1970s and 1980s have shown that the abatement costs are substantial, but did not account for the benefits of environmental improvements (Jorgenson and Wilcoxen, 1990).

2 Empirical Setting

The Clean Air Act is the primary air quality legislation in the United States. Originally passed in 1963, it established several federal programs to address air pollution, including research, monitoring, and abatement. Since its implementation, there have been three major sets of amendments in 1970, 1977, and 1990 which enhance the ability of the federal and state governments to regulate and restrict emissions. Currie and Walker (2019) provide an overview of what we have learned about the economics of the Clean Air Act in recent decades.

The main air pollution regulations under the Clean Air Act are the National Ambient Air Quality Standards (NAAQS) introduced as part of the 1970 amendments. The original NAAQS set federal standards on ambient concentrations for a set of five criteria air pollutants: ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), and total suspended particulates (TSP). States were required to enforce these standards through their own abatement programs under the 1970 CAAAs. If a county is found to be in nonattainment in a particular year — effectively meaning the county violated the NAAQS for a particular pollutant — then states were mandated to regulate plant-level sources of these pollutants.

The 1977 amendments introduced additional regulation. States were newly required to develop a state implementation plan (SIP) upon nonattainment designation, which outlines how the state will bring the county back into attainment. Following approval of a SIP, the Environmental Protection Agency is empowered to use sanctions as a means of enforcement. In addition, the 1977 CAAAs limit entry of new pollution sources in nonattainment areas. Any new or modified source of criteria pollution are mandated to be at the lowest achievable emissions rate (LAER) in nonattainment counties, while attainment counties require only the best available control technology (BACT). Despite the absence of uniform standards for these technologies, LAER is generally acknowledged the strictest level of emission reductions under the NAAQS. In nonattainment counties under LAER, abatement expenditures and total operating costs of plants tend to be higher (Becker and Henderson, 2001; Becker, 2005). Nonattainment status also decreases new plant openings and the movement of plants to counties that were historically in attainment (Henderson, 1996; Becker and Henderson, 2000), providing some evidence for reallocation in response to nonattainment.

The most recent amendments in 1990 replaced TSP as a criteria pollutant with particulate matter with a diameter 10 micrometers or less (PM_{10}), began regulating toxics, introduced new cap and trade programs, modified gasoline standards, and reviewed nonattainment designations across air regions (Currie and Walker, 2019). Following the recent literature, we exploit variation in the nonattainment status due to the heightened regulatory scrutiny following the passage of the 1990 CAA amendments and their subsequent enforcement (Grainger, 2012; Walker, 2013; Bento et al., 2015). Particularly important for our empirical analysis — although the amendments were passed in 1990 — counties newly in nonattainment were only formally designated as in nonattainment in 1991 (United States Federal Register, 1993).

3 Model

We develop a Ricardian model of interregional trade for the United States in the spirit of Eaton and Kortum (2002). In the model, there are N counties indexed by i, j, n, and K industries indexed by k, l, m. Firms use labor and capital as inputs into production. Production generates emissions — or isomorphically, emissions are an input to production (Copeland and Taylor, 2013) — and firms face an implicit price of emissions from the prevailing set of local environmental regulations. Labor is supplied inelastically and is imperfectly mobile across locations and industries; capital is perfectly mobile so that the rental rate is equalized across locations.

Differences in productivity and implicit emissions prices across counties and industries determine the allocation of labor and emissions, and hence the spatial and sectoral distribution of economic activity. In our model, we incorporate nonattainment designation that affect both the implicit price of emissions and factor productivity in the polluting sector. We take nonattainment designations to be exogenous so that reallocation of emissions across space does not endogenously induce a county to be in nonattainment.[6]

3.1 The Household Problem

There is a mass L_j^m of households in each location j and industry m. We call (j, m) location-industry pairs *markets*. Households maximize a Cobb-Douglas utility function by choosing a market (i, k) to work and live, and then allocating their competitive wage w_i^k over a set of local final goods C_i^l:

$$U_j^m = \max_{i \in N, k \in K} \; B_i \delta_{ji}^{mk} \prod_{l=1}^{K} \left(C_i^l\right)^{\alpha^l}.$$

[6]The main reason we do not consider endogenous nonattainment is that thresholds are relatively complicated and difficult to represent within the model which is quantified using annual data. For example, a county is designated in nonattainment for NO_2 if the 98th percentile of 1-hour daily maximum concentrations, averaged over 3 years, is above 100 parts per billion.

where C_i^l is a constant elasticity of substitution (CES) aggregate of industry l varieties with an elasticity of substitution of σ^l. The parameter α^l is the consumption share of industry l where $\sum_{l=1}^{K} \alpha^l = 1$ and $\delta_{ji}^{mk} \in (0, 1]$ is the cost of moving from market-industry pair (j, m) to market-industry (i, k) in consumption terms. The price index in county i for the aggregate final good C_i is given by:

$$P_i \equiv \prod_{k=1}^{K} \left(P_i^k / \alpha^k\right)^{\alpha^k}$$

where P_i^k is the CES price index of goods purchased from industry k for final consumption in county i that we will define below. A consumer's real wage V_i^k is defined as:

$$V_i^k = \frac{w_i^k}{P_i}.$$

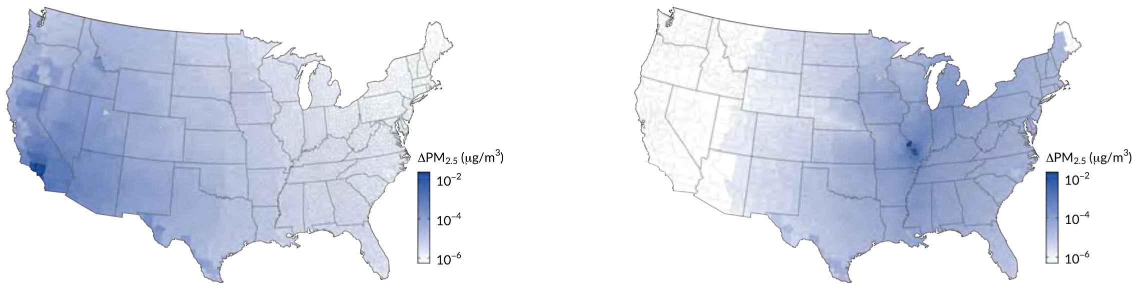
The B_i term in consumer utility captures amenities in location i and is common across workers in each location. These location-specific amenities are determined by a host of local factors including ambient pollution concentrations.[7] Local ambient pollution y_i is a function of emissions in all locations: $y_i = Y_i(\boldsymbol{e})$ where $\boldsymbol{e} = (e_1^1, \ldots, e_N^1, \ldots, e_1^2, e_N^2, \ldots, e_1^P, \ldots, e_N^P)$ is a vector of emissions e_i^p of pollutant p in location i where there are P different kinds of emitted pollutants and $p = 1, \ldots, P$.[8] This setup reflects two features that are relevant in our empirical setting. First, different emitted pollutants may contribute to the ultimate formation of ambient pollution y_i. For example, ammonia, nitrogen oxides, and volatile organic compounds are precursors to ambient particulate matter, while nitrogen oxides and volatile organic compounds are precursors to ambient ozone. Second, emissions can be distributed across counties, and therefore affect ambient concentrations and amenities in other locations, imposing cross-county externalities.

We specify Y_i as the atmospheric transportation model in AP3 (Muller and Mendelsohn, 2009; Muller, Mendelsohn and Nordhaus, 2011; Tschofen, Azevedo and Muller, 2019), a widely used integrated assessment model for measuring the economic damages from emissions of air pollutants. The atmospheric transportation model simulates how one ton of pollutant p emitted in any county i translates into changes in ambient concentrations in all counties in

[7] An alternative approach is to specify a reduced-form relationship between local amenities (B_i) and nonattainment status. This provides a separate theoretical representation of amenities and implies a different empirical approach to quantifying the the effect nonattainment on amenities. Our preferred approach is to incorporate emissions directly. That said, in Appendix A, we discuss the alternative reduced-form method as well as the associated empirical and counterfactual results. In general, our results are robust to this alternative formulation.

[8] In this formulation, we focus on a single ambient pollutant. However, it is straightforward to incorporate multiple types of ambient pollution.

Figure 1: Change in $PM_{2.5}$ concentrations in micrograms per cubic meter from one thousand metric tons of NO_x emissions in Los Angeles and St. Louis.



Note: The maps show the distribution changes in $PM_{2.5}$ concentrations from one thousand metric tons of nitrogen oxides emissions from Los Angeles County, CA (left panel) and St. Louis County, MO (right panel). The units for the change in $PM_{2.5}$ is micrograms per cubic meter.

the United States.[9] Figure 1 provides two examples to illustrate the geographic structure of Y_i. The figure shows how one thousand metric tons of emissions of nitrogen oxides, a $PM_{2.5}$ precursor, affects nationwide $PM_{2.5}$ concentrations differently depending on the location of emission. The figure shows that the effect of emissions on concentrations declines roughly exponentially in space.

Moving from emissions to amenities requires translating changes in concentrations into consumption-equivalent terms. We do this by drawing on the dose-response model in AP3 that maps changes in local ambient pollution into monetized damages. We translate monetized damages into relative consumption-equivalent terms by expressing them as a fraction of real wages. The location of emissions relative to population centers and how emissions are transported across space determine how pollution externalities affect local amenities. In turn, this will affect the distribution of impacts of reallocation in response to nonattainment.

Labor is mobile across counties, but moving from (j, m) to (i, k) incurs a utility cost $\delta_{ji}^{mk} \in (0, 1]$ where $\delta_{jj}^{kk} = 1$ for all $j = 1, \ldots, N$ and $k = 1, \ldots, K$. Moving costs have a deterministic component $\bar{\delta}_{jn}^{ml}$ and an idiosyncratic random component ε:

$$\delta_{jn}^{ml} = \bar{\delta}_{jn}^{ml} \varepsilon$$

where ε has the commonly assumed extreme value distribution. This implies the share of

[9] The dispersion of emissions is represented as linear system so that boils down to an $N \times N$ matrix that predicts how a ton of emissions in some source county changes concentrations in a receptor county.

households that migrate from (j,m) to (i,k) is:

$$\pi_{ji}^{mk} = \frac{\frac{w_i^k}{P_i} B_i \bar{\delta}_{ji}^{mk}}{\sum_{n=1}^{N} \sum_{l=1}^{K} \frac{w_n^l}{P_n} B_n \bar{\delta}_{jn}^{ml}}. \tag{1}$$

This reflects that a household moving from (j,m) to (i,k) does so if (i,k) has the highest indirect utility from consumption and amenities after accounting for moving costs. The value of consumption and amenities in each location will be determined by the endogenous reallocation of labor and emissions across space. In Section A of the appendix we use the structure of the household problem to estimate household migration responses to nonattainment as validation for our approach. First, we show that households actually respond to changes in nonattainment status by moving. Second, we estimate the reduced-form *total* effect of a county's nonattainment status on its own amenities. Since the change in relative migration flows capture all of the possible pathways through which nonattainment status improves local amenities this provides an upper bound on the size of the amenities effect in our quantitative exercises.

3.2 The Firm Problem

Following the approach in Copeland and Taylor (2013), perfectly competitive firms use a Cobb-Douglas technology to produce different varieties of goods by combining labor $L_i^k(\omega)$ and capital $K_i^k(\omega)$, net of abatement of emissions $a_i^{kp}(\omega)$:

$$q_i^k(\omega) = \left[\prod_{p=1}^{P}(1 - a_i^{kp}(\omega))\right] \left[z_i^k(\omega)\, [K_i^k(\omega)]^{1-\gamma}\, [L_i^k(\omega)]^{\gamma}\right]$$

where ω denotes different varieties, p indexes different pollutants $p = 1, \ldots, P$, $z_i^k(\omega)$ is variety-specific productivity, $\gamma \in [0,1]$ is the labor share, and capital is perfectly mobile across space and sectors. To simplify the exposition, from hereon we omit varieties from the notation whenever the mathematics remain clear.

3.2.1 Emissions

Emissions e_i^{kp} of pollutant p by industry k in county i are produced according to the following technology:

$$e_i^{kp} = (1 - a_i^{:p})^{1/\xi^{kp}} z_i^k\, (K_i^k)^{1-\gamma}\, (L_i^k)^{\gamma}$$

where $\xi^{kp} \in [0,1]$ is the pollution elasticity and $\sum_{p=1}^{P} \xi^{kp} \in [0,1]$. Combining the previous two expressions shows that this model is isomorphic to one where the firm operates a two-tier Cobb-Douglas technology using emissions of each pollutant as an input (Copeland and Taylor, 2013):

$$q_i^k = \left[\prod_{p=1}^{P} \left(e_i^{kp} \right)^{\xi^{kp}} \right] \left[z_i^k \left(K_i^k \right)^{1-\gamma} \left(L_i^k \right)^{\gamma} \right]^{1-\sum_{p=1}^{P} \xi^{kp}}$$

and one unit of output generates one unit of emissions subject to the appropriate normalization. Under a Cobb-Douglas production technology, the emissions intensity of output for pollutant p is given by:

$$\frac{e_i^{kp}}{q_i^k} = \frac{\xi^{kp} P_i^k}{\eta_i^{kp}} \tag{2}$$

where P_i^k is the industry price index which we define below and η_i^{kp} is the exogenously given implicit marginal cost or price of emissions faced by the firm for pollutant p. For all $\eta_i^{kp} \leq \xi^{kp} P_i^k$, we let $\frac{e_i^{kp}}{q_i^k} = 1$ since that is the unconstrained emission intensity in the absence of an emission price. We parameterize η_i^{kp} to be a function of nonattainment status $N_i \in \{0,1\}$ as well as other overlapping environmental regulations that disincentivize emissions. Formally, we let,

$$\eta_i^{kp}(N_i) = \bar{\eta}_i^{kp} \exp\left(\beta_\eta^p N_i \right)$$

where $\bar{\eta}_i^{kp}$ captures the impact of forces other than nonattainment. We estimate β_η^p, which is the effect of nonattainment on the emissions price in percentage terms.

3.2.2 Productivity

For each market, $z_i^k(\omega)$ is efficiency or the quantity of variety ω within industry k that can be produced using one unit of labor, capital, and emissions in county i and industry k. Following Eaton and Kortum (2002), we assume that $z_i^k(\omega)$ is a random variable distributed according to the Fréchet distribution:

$$F_i^k(z) = \exp\left(-T_i^k z^{-\theta^k} \right) \tag{3}$$

where $\theta^k > 1$ is the trade elasticity parameter common across all counties and measures the level of intra-industry heterogeneity. Smaller values of θ^k indicate more heterogeneity and a greater role for comparative advantage. T_i^k measures fundamental productivity, where higher values increase the probability of larger efficiency draws $z_i^k(\omega)$ and indicates (i,k) has greater absolute advantage.

The fundamental productivity of county i has two parts:

$$T_i^k = \bar{T}_i^k \exp\left(\beta_T^k N_i\right). \tag{4}$$

The first part, $\bar{T}_i^k$, is the market's base productivity, which captures standard components of technological know-how and exogenous location-specific factors. The second part, $\exp(\beta_T N_i)$, is a function of the county's nonattainment status N_i. We estimate the parameter $\beta_{\mathbf{T}}^{\mathbf{k}}$ to recover the effect of regulation on productivity. We assume $\beta_{\mathbf{T}}^{\mathbf{k}} = 0$ for the non-polluting sector since nonattainment only affects polluters.

We allow for nonattainment to directly affect firm productivity in light of evidence that environmental regulation can reduce productivity (e.g. Brännlund, Lundgren et al., 2009; Ambec, Cohen, Elgie and Lanoie, 2013; Greenstone, List and Syverson, 2012).[10] There are several channels through which nonattainment designations may reduce productivity. For example, plant inspections for violations — which are more common in nonattainment areas — may require costly plant shutdowns which will be reflected as declines in factor productivity. Alternatively, fines, sanctions, legal costs, and other costs outside the scope of our model are also captured as decreases in productivity. In addition, LAER abatement technology mandates may require firms to adopt new production processes that are less efficient in their use of inputs, even after holding emissions constant. We test whether these channels matter empirically below.

3.2.3 Prices and Market Clearing

The price of an input bundle for market (i,k) is:

$$c_i^k = \left[\prod_{p=1}^{P}\left(\eta_i^{kp}\right)^{\xi^{kp}}\right]\left[(r_i^k)^{1-\gamma}\,(w_i^k)^{\gamma}\right]^{1-\sum_{p=1}^{P}\xi^{kp}}, \tag{5}$$

where the assumption of perfect capital mobility implies that $r_i^k = r$ for all i,k.

Trade costs take the iceberg form, which requires shipping $\tau_{ij}^k \geq 1$ units of the good from county j to county i for 1 unit to be delivered and we assume that $\tau_{jj}^k = 1$ for all j,k. The

[10]The weak form of the Porter Hypothesis states that regulation leads to increased innovation is supported by a large body of evidence. There is limited evidence for the strong form of the Porter Hypothesis, which states that regulation leads to increased productivity (Brännlund, Lundgren et al., 2009; Ambec, Cohen, Elgie and Lanoie, 2013).

ideal price index can be shown to be:

$$P_i^k = \kappa \left(\sum_{n=1}^{N} \left(T_n^k\right)^{1-\sum_{q=1}^{P} \xi^{kq}} \left[c_i^k \tau_{in}^k\right]^{-\theta^k} \right)^{-1/\theta^k} \tag{6}$$

where κ is a constant and the fundamental productivity term is raised to $1-\sum_{q=1}^{P} \xi^{kq}$ because it augments the productive factors. A transformation of the price index, $\left(P_i^k\right)^{-\theta^k}$, is called consumer market access (CMA_i^k) and captures county i's access to cheaper products. An analogous term for the firm side is firm market access:

$$FMA_i^k = \sum_{j=1}^{N} \frac{\tau_{ji}^{-\theta^k} Y_j^k}{CMA_j^k} \tag{7}$$

which captures firms' access to larger markets. These terms are equivalent up to a normalization and we define market access MA_i^k as:[11]

$$MA_i^k \equiv FMA_i^k = \rho CMA_i^k$$

where ρ is a constant.

Bilateral trade expenditures for county i on goods from county j are given by:

$$X_{ij}^k = \kappa T_j^k Y_i^k \left(\frac{c_j^k \tau_{ij}^k}{P_i^k} \right)^{-\theta^k}. \tag{8}$$

We denote trade shares as:

$$\lambda_{ij}^k = \frac{X_{ij}^k}{\sum_{h=1}^{N} X_{ih}^k} \tag{9}$$

and total expenditures as:

$$X_i^k = \sum_{h=1}^{N} X_{ih}^k. \tag{10}$$

Finally, labor market clearing requires:

$$w_i^k L_i^k = \gamma \left(1 - \sum_{p=1}^{P} \xi^{kp}\right) \sum_{h=1}^{N} X_h^k \lambda_{hi}^k. \tag{11}$$

[11] For example see, Anderson and Van Wincoop (2003) or Donaldson and Hornbeck (2016).

Equilibrium Definition: Given model primitives T_i^k, B_i^k, L_i^k, τ_{ij}^k, $\bar{\delta}_{ij}^{km}$, N_i, and η_i^{kp}, an equilibrium is a vector of wages $\{w_i^k\}$ and prices $\{P_i^k\}$ for $i = 1, \ldots, N$ and $k = 1, \ldots, K$ such that equations (1) through (11) are satisfied.

4 Data

The data for this paper are drawn from several sources. This includes information on nonattainment status and emissions, economic activity including the wage bill and the number of workers by polluting and nonpolluting sectors, and geographic and sectoral mobility. Finally, we use new data on historical trade costs via the highway network to calculate market access. We collect this information for US counties with consistently defined geographic boundaries over our sample period from 1986 to 1997.

4.1 Nonattainment Status

Data on the Clean Air Act and county nonattainment status come from the US Environmental Protection Agency Greenbook. The Greenbook reports which counties are in nonattainment under a given regulatory standard in each year. In particular, the data include whether a county is in full or partial nonattainment for each of O_3, NO_2, SO_2, CO, PM_{10}, and $PM_{2.5}$. We treat full and partial nonattainment status as equivalent when assigning treatment status. Consistent nonattainment designations are available from 1978 to the present. Our productivity analysis focuses on the period between 1986 and 1997, which allow for five periods before and after new nonattainment designations under the 1990 CAA amendments. For robustness, in Section C of the appendix, we consider alternative sample periods.

4.2 Emissions

Data on emissions come from the National Emissions Inventory (NEI). The NEI reports emissions at point sources of a wide range of pollutants. We limit our focus to emissions from the manufacturing sector of ammonia (NH_3), nitrogen oxides (NO_x), particulate matter smaller than 2.5 micrometers ($PM_{2.5}$), sulfur dioxide (SO_2), and volatile organic compounds (VOCs). These are the pollutants that are reported in the NEI and accounted for in the AP3 model as precursors of particular matter. Our main estimates for effects on emissions use data in 1990 and 1996–2001, although in C of the appendix we use shorter panels to test for robustness and more closely match the productivity analysis.

4.3 Economic Activity by Sector

We draw on data from the Bureau of Economic Analysis to capture county-level economic activity by industry. Specifically, we use information on payroll and employment by industry each year from 1986 to 2001. We aggregate the industry-level data to groups that encompass polluting and nonpolluting sectors. For the polluting sector, we focus on employment in manufacturing. For the nonpolluting sector, we include employment in industries not in manufacturing and also exclude utilities. Utilities are the primary industry covered by the Acid Rain Program — another new regulation under the 1990 CAA amendments. Our focus in this paper is on environmental regulation stemming from the NAAQS.

4.4 Geographic and Sectoral Mobility

We compute cross-county migration shares using tax return data from the Internal Revenue Service's (IRS) SOI Tax Stats data. The IRS reports tax return level counts of bilateral county-to-county flows each year starting in 1990 (US Internal Revenue Service, 2021). We use returns as our measure of workers rather than exemptions so that we avoid counting dependents as workers. One limitation of the IRS data is that it does not contain information on mobility across sectors. We compute cross-sector mobility shares using data from the Public Use Microdata Sample of the Current Population Survey (US Census Bureau, 2021). The Current Population Survey reports monthly individual level data on the industry of employment among other variables. The Current Population Survey follows individuals for four months, and then another four months with an eight month gap in between the two spells. We use the industry of employment in the first month of each four month spell for each individual, and then aggregate this up to a national level to compute national mobility shares across the polluting and non-polluting sector. For the counterfactual simulations, we construct the full mobility share matrix by taking the Kronecker product of the county migration matrix and the sectoral mobility matrix as in Caliendo, Dvorkin and Parro (2019) and Rudik, Lyn, Tan and Ortiz-Bobea (2021). The lack of a combined migration and sectoral mobility data requires us to implicitly assume that movers and stayers have the same probabilities of changing their sector of employment.

4.5 Bilateral Trade Costs and Market Access

To capture spatial linkages between counties due to interregional trade, we construct the "market access" variable implied by the theory. The key input is a measure of trade costs and that we construct following the approach in (Combes and Lafourcade, 2005). To start, we find the lowest travel time route between all county pairs in 1980, 1990, and 2000. To do this we combine newly digitized shapefiles of the US highway network in each year between 1980 and 1990 (Jaworski and Kitchens, 2021) with readily available shapefiles for the US highway network in 2000 (US Department of Transportation, 2021) and use Djikstra's algorithm to find the lowest-travel time route between all county pairs in each year. We record travel time (in hours) and distance (in miles) associated with each route.

To construct trade costs for a given year we assign the travel times and distances from the closest year (e.g., highway data from 1980 is assigned to 1982, highway data from 1990 is assigned to 1987, etc.) as well as fuel costs measured by the national fuel price and contemporary vehicle efficiency and labor costs measured by the hourly wage of a truck driver in each year. To convert these monetary values into iceberg trade we divide by the average value of a shipment from the Commodity Flow Survey in 2012. This yields a symmetric matrix of bilateral trade costs between all county pairs.

We then combine trade cost and employment data to construct market access for each year by solving the system of equations given by: $MA_i^k = \rho_2 \sum_{j=1}^{N} \tau_{ji}^{-\theta^k} \left(MA_j^k\right)^{-1} w_j^k L_j^k$, where τ_{ji} is the matrix for trade costs and $w_j^k L_j^k$ is the sector-specific wage bill.[12] This requires calibrating the trade elasticity (θ^k), which we set to 4 as described below. We also consider robustness to alternative values.

5 Estimating the Effects of Nonattainment Status

The spatial equilibrium model in Section 3 is useful as a guide for estimating the impact of nonattainment in an internally consistent way. The model makes explicit that nonattainment status increases the implicit price of emissions and reduces productivity in the polluting sector. All else equal, this decreases the quantity of emissions in nonattainment counties and reallocates labor across counties and industries, which causes changes in emissions and ambient pollution concentrations and amenities in all counties. This induces migration of households to areas with relatively better amenities. Finally, production and household decisions are further affected by trade and mobility costs. In this section, we derive our estimating equations to illustrate how spatial and intersectoral linkages have potentially important consequences for estimating the parameters of interest, i.e., β_η^p and β_T^k.

[12] This is a version of the system expressed in equation (7). The solution to this system is unique up to a constant.

5.1 Emissions

We first estimate the effect of nonattainment status on the local implicit emissions price. We use equation (2) together with the expression for labor's fixed share of firm revenues, $\gamma\left(1-\sum_{q=1}^{P}\xi^{kq}\right)$, to obtain an expression for emissions as a function of nonattainment status, the endogenous industry wage bill, emissions elasticities, and the unobserved base emissions price:

$$\log\left(e_i^{kp}\right) = \underbrace{-\beta_\eta^p N_i}_{\text{nonattainment}} + \underbrace{\log\left(w_i^k L_i^k\right)}_{\text{wage bill}} + \underbrace{\log\left(\frac{\xi^{kp}}{\gamma\left(1-\sum_{q=1}^{P}\xi^{kq}\right)}\right)}_{\text{emissions elasticities}} - \underbrace{\log\left(\bar{\eta}_i^{kp}\right)}_{\text{emissions price}}.$$

We estimate difference-in-differences specifications that exploit variation in nonattainment status at the county level over time. Following the previous literature, we focus on the quasi-experimental assignment of nonattainment status caused by the 1990 CAA amendments (Grainger, 2012; Walker, 2013; Bento et al., 2015). The identifying variation for the effect of nonattainment on emissions comes from comparing emissions in attainment versus nonattainment counties, before and after a new nonattainment designation under the 1990 CAA amendments. Including the wage bill is theoretically important because it controls for how nonattainment will indirectly affect emissions through productivity. This allows us to separate the technique effect from the scale and composition effects since conditioning on the wage bill holds output and goods prices fixed in a Cobb-Douglas setting so the only change is in emissions relative to output. Omitting the wage bill term will potentially confound changes in implicit emissions prices with changes in productivity of labor and capital.

Our estimating equation is:

$$\log\left(e_{i,t}^{p}\right) = -\beta_\eta^p N_{i,t} + \log\left(w_{i,t} L_{i,t}\right) + \psi_i + \nu_{p,t} + \varepsilon_{is,t}^{p} \tag{12}$$

where t indexes time reflecting our panel dataset. Our preferred approach is to estimate a single specification that captures pollutant-specific effects of nonattainment status since there is significant heterogeneity in the amenity effects and response to nonattainment of each pollutant, but we also estimate a combined effect as a robustness check.

We consider specifications that omit the wage bill for the polluting sector entirely, specifications that include the wage bill and estimate the coefficient, and specifications that include the wage bill and fix the coefficient at 1 to be consistent with the theory. Our preferred approach is the last one so the empirics match the model as closely as possible. Next, we use county (ψ_i), pollutant-year ($\nu_{p,t}$), and state-by-year ($\nu_{s,t}$) fixed effects to control for the unobserved base implicit emissions price induced by other overlapping environmental regulations. There are still two remaining threats to identification: increased economic growth causing more emissions and inducing nonattainment, and a SUTVA violation where nonattainment induces emissions leakage to attainment counties. The first threat is addressed by the wage bill control which essentially holds the size of the local economy fixed. The second threat can be assessed by the quantitative model which suggests that there is actually a small amount of negative leakage so that our estimates here may be slightly biased toward zero.

Note we are not able to estimate event study specification since the National Emissions Inventory data only have one pre-period for all counties in 1990. Thus, we only consider difference-in-difference specifications that compare counties in nonattainment due to the 1990 Clean Air Act Amendments in 1990 (before) versus 1996 and later (after). Standard errors are clustered at the county level to address within county correlation of emissions over time.

Table 1 reports our estimates based on equation (12). Panel A reports the average effect of any nonattainment designation across all criteria pollutant types. Column 1 includes county and pollutant-year fixed effects. Column 2 adds the wage bill for the polluting sector, where the coefficient is determined by the data, while Column 3 fixes the coefficient to be consistent with the theory. Finally, Column 4 includes state-year fixed effects. The results across all four columns are highly consistent and indicate that nonattainment raises the implicit price or marginal cost of emissions by 42–45 percent.[13] Note that since the estimates are large, the percentage effect is given by $\exp(\beta) - 1$ and the small value approximation of β^p_η is not valid.

Panel B repeats the same exercise as Panel A, but where we estimate pollutant-specific effects of nonattainment designation. The estimates in Panel B show similar robustness to those in Panel A, and they also highlight the extensive heterogeneity in the effect of nonattainment on emissions of different pollutants. The price of emissions on ammonia goes up by over 500 percent, the prices of nitrogen oxides and volatile organic compounds go up by over 50 percent, and the prices of fine particulates and sulfur dioxide go by about 25 percent. The large ammonia effect is consistent with evidence that marginal abatement costs for ammonia are low compared to other particulate precursors (Gu et al., 2021).

5.2 Productivity

We estimate the effect of nonattainment status on local productivity in two steps. We first estimate a composite effect of nonattainment and both productivity and the implicit emis-

[13]The estimated coefficient on the log wage bill is about 0.25 for both panels.

Table 1: Estimated Effect of Nonattainment on the Implicit Emissions Price

	(1)	(2)	(3)	(4)
A. Combined				
β_η^p	0.35^{**}	0.35^{**}	0.37^{**}	0.37^{**}
	(0.15)	(0.15)	(0.15)	(0.15)
B. By Emitted Pollutant				
Ammonia ($\beta_\eta^{NH_3}$)	2.0^{***}	2.0^{***}	2.0^{***}	1.9^{***}
	(0.39)	(0.39)	(0.39)	(0.39)
Nitrogen Oxides ($\beta_\eta^{NO_x}$)	0.47^{**}	0.47^{**}	0.49^{***}	0.52^{***}
	(0.19)	(0.19)	(0.19)	(0.19)
Fine Particulates ($\beta_\eta^{PM_{2.5}}$)	0.17	0.17	0.19	0.21
	(0.26)	(0.27)	(0.28)	(0.28)
Sulfur Dioxide ($\beta_\eta^{SO_2}$)	0.24	0.24	0.26	0.25
	(0.21)	(0.21)	(0.21)	(0.21)
Volatile Organics (β_η^{VOC})	0.42^{**}	0.42^{**}	0.44^{**}	0.42^{**}
	(0.20)	(0.20)	(0.20)	(0.20)
Observations	70,225	70,225	70,225	70,225
County Fixed-Effects	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	No
Pollutant Fixed-Effects	Yes	Yes	Yes	No
Pollutant-Year Fixed-Effects	No	No	No	Yes
Wage Bill	Omitted	Coef. Free	Coef. Fixed	Coef. Fixed

Note: The table shows estimates for versions of equation (12). The dependent variable is the log of emissions in all columns. Panel A reports estimates of the coefficient on nonattainment status determined by exceeding the regulated threshold for any pollutant. Panel B reports estimates of the coefficient on nonattainment status determined by the exceeding the threshold for the specified pollutant. Column 1 only includes county, year, and pollutant fixed effects; Column 2 adds the wage bill where the coefficient is estimated; Column 3 includes the wage bill where the coefficient is fixed at its theoretical value; Column 4 replaces year and pollutant fixed effects with pollutant year fixed effects. Robust standard errors clustered at the county level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

sions price, then we use our emissions estimates above to isolate the effect on productivity. We start by combining equations (6), (9), and (11) to obtain an condition for equilibrium industry income:

$$Y_i^k = \frac{w_i^k L_i^k}{\gamma\left(1-\sum_{q=1}^{P}\xi^{kq}\right)} = \sum_{j=1}^{N} X_{ji}^k = T_i^k\left(c_i^k\right)^{-\theta^k} MA_i^k.$$

Following Walker (2013), we estimate triple-difference specifications that exploit variation in nonattainment status at the county level over time as well as variation across polluting versus non-polluting industries within each county. Similar to our approach for emissions, we use the quasi-experimental variation from counties newly assigned to nonattainment under the 1990 CAA amendments. The identifying variation for the effect of nonattainment on productivity comes from comparing polluting sectors subject to nonattainment enforcement to non-polluting sectors in attainment versus nonattainment counties, before and after a county enters nonattainment.[14]

Substituting in the expression for the input cost bundle in equation (5), taking the logarithm of both sides, and rearranging gives the log of industry income as a function of nonattainment status, an adjustment for endogenous and observable industry real wages, emissions elasticities, and the unobservable base productivity and emissions price (i.e., the components not due to nonattainment):

$$\begin{aligned}\log\left(\frac{w_i^k L_i^k}{\gamma\left(1-\sum_{q=1}^{P}\xi^{kq}\right)}\right) \quad &= \quad \underbrace{\left(\beta_T - \theta^k\sum_{p=1}^{P}\eta^{kp}\beta_\eta^p\right)N_i}_{\text{nonattainment}} \quad - \quad \underbrace{\theta^k\log\left(\frac{\tilde{w}_i^k}{P_i}\right)}_{\text{real wage adjustment}} \\ &\quad - \quad \underbrace{\theta^k(1-\gamma)\left(1-\sum_{q=1}^{P}\xi^{kq}\right)\log(r)}_{\text{elasticities and common rental rate}} \quad + \quad \underbrace{\log\left(\bar{T}_i^k\right) - \theta^k\alpha\log\left(\bar{\eta}_i^k\right)}_{\substack{\text{base productivity}\\ \text{and emissions price}}}\end{aligned}$$

where $\tilde{w}_i^k = {w_i^k}^{\gamma\left(1-\sum_{q=1}^{P}\xi^{kq}\right)}$.

The estimating equation is given by:

$$\log\left(w_{i,t}^k L_{i,t}^k\right) = \left(\beta_T - \theta^k\sum_{p=1}^{P}\eta^{kp}\beta_\eta^p\right)N_{i,t} - \theta^k\log\left(\frac{\tilde{w}_{i,t}^k}{P_{i,t}}\right) + \psi_i^k + \nu_t^k + \iota_{i,t} + \varepsilon_{i,t}^k. \tag{13}$$

The estimated coefficient on nonattainment status, $\left(\beta_T - \theta^k\sum_{p=1}^{P}\eta^{kp}\beta_\eta^p\right)$, reflects a com-

[14] Walker (2013) compares establishments designated as polluters to those who are not polluters, in nonattainment versus attainment counties, before and after county nonattainment designation. Consistent with our model, we focus on industry outcomes by county and year.

posite effect on productivity and the implicit emissions price, and a composite of the scale, composition, and technique effects since β_η^p picks up the technique effect, and a reduction in productivity in one industry raises economy-wide costs (scale effect), and leads to a reallocation of productive factors across industries (composition effect). Using our estimates of β_η^p above, we can isolate β_T which will capture a composite of scale and composition effects. $\exp(\beta_T)$ gives us the reduction (in percent) in the location parameter of the Fréchet distribution, which governs the county-industry productivity and, therefore, the extent of absolute advantage.

The theory suggests that the coefficient on the real wage is equal to the trade elasticity, θ^k. In practice, we consider alternative approaches that omit real wages from the estimating equation, estimate the coefficient on real wages, or set the coefficient equal to the value consistent with the theory. Our preferred approach to fix the value of θ^k at 4, which is drawn from Simonovska and Waugh (2014). We also fix the ξ^{kp} elasticities. We fix the elasticities for NO_x, $PM_{2.5}$, SO_2, and VOCs at the median industry-specific values estimated by Shapiro and Walker (2018). We fix the value for NH_3 to their estimate for $PM_{2.5}$ since no direct estimate for NH_3 is available and $PM_{2.5}$ is the broadest category of pollution. We assume that the non-polluting sector has no emissions and therefore that these elasticities are zero. The values of these elasticities are reported in Table 3. Table A4 in the appendix shows that our estimates are robust to other choices of trade and pollution elasticities.

The remaining terms on the right-hand of equation (13) are industry-county (ψ_i^k), industry-year (ν_t^k), and county-year ($\iota_{i,t}$) fixed effects that capture variation in the rental rate, base productivity, and the emissions price. In addition to our main triple-difference specifications we also estimate event study specifications to understand changes over time, test the identifying assumption underlying the triple-differences approach, and to compare to the existing literature. We cluster standard errors at the county level to allow for correlation within counties across sectors and over time.

Table 2 reports our estimate of $\left(\beta_T - \theta^k \sum_{p=1}^{P} \eta^{kp} \beta_\eta^p\right)$ building on equation (13). Panel A contains estimates of the impact of being in nonattainment for any pollutant, while Panel B shows the effect of being in nonattainment for each relevant criteria pollutant. The first column is our baseline specification that includes county-industry, industry-year, and nonattainment status-year fixed effects, but with the adjusted real wage variable omitted. The second column adds the adjusted real wage variable, but allows the coefficient to be determined by the data.[15] The third columns fixes the coefficient on the adjusted real variable variable to be consistent the theory. The final column is our preferred specification, which replaces nonattainment status-year fixed effects with county-year fixed effects.

[15] The estimate of θ^k in each panel is about 0.5.

Table 2: Estimated Effect of Nonattainment on Productivity.

	(1)	(2)	(3)	(4)
A. Combined				
$\beta_T - \theta^k \sum_{p=1}^{P} \eta^{kp} \beta_\eta^p$	-0.074^{**}	-0.059^{**}	-0.099^{**}	-0.091^{**}
	(0.031)	(0.026)	(0.049)	(0.036)
B. By Ambient Pollutant				
Carbon Monoxide Nonattainment (CO)	-0.030	-0.011	-0.062	-0.057
	(0.153)	(0.102)	(0.244)	(0.079)
Ozone/Nitrogen Dioxide Nonattainment (O_3/NO_2)	-0.064^{*}	-0.070^{***}	-0.054	-0.046
	(0.033)	(0.027)	(0.051)	(0.037)
Particulate Matter Nonattainment (PM_{10})	-0.107^{***}	-0.074^{***}	-0.163^{***}	-0.155^{***}
	(0.030)	(0.028)	(0.048)	(0.036)
Sulfur Dioxide Nonattainment (SO_2)	-0.147^{***}	-0.144^{***}	-0.151^{***}	-0.145^{***}
	(0.008)	(0.006)	(0.015)	(0.015)
Observations	72,279	72,279	72,279	72,279
Industry-County Fixed-Effects	Yes	Yes	Yes	Yes
Industry-Year Fixed-Effects	Yes	Yes	Yes	Yes
CO Nonattainment-Year Fixed-Effects	Yes	Yes	Yes	No
O_3/NO_2 Nonattainment-Year Fixed-Effects	Yes	Yes	Yes	No
SO_2 Nonattainment-Year Fixed-Effects	Yes	Yes	Yes	No
PM_{10} Nonattainment-Year Fixed-Effects	Yes	Yes	Yes	No
County-Year Fixed-Effects	No	No	No	Yes
Real Wage	Omitted	Coef. Free	Coef. Fixed	Coef. Fixed

Note: The table shows estimates for versions of equation (13). The dependent variable in all columns is the log of industry income. Panel A reports estimates of the coefficient on nonattainment status determined by exceeding the regulated threshold for any pollutant. Panel B reports estimates of the coefficient on nonattainment status determined by the exceeding the threshold for the specified pollutant. Column 1 only includes industry-county, industry-year, and pollutant-year fixed effects; Column 2 adds the adjusted real wage the coefficient is estimated; Column 3 includes the adjusted real wage where the coefficient is fixed at its theoretical value; Column 4 replaces pollutant-year fixed effects with county-year fixed effects. Robust standard errors clustered at the county level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Panel A, the estimated coefficient in Column 1 is -0.074, which indicates a reduction in industry income associated with a nonattainment designation that could be arising from either increases in implicit emissions prices or decreases in productivity. The magnitude of the estimated coefficient decreases in Column 2 (-0.059) after controlling for the adjusted real wage variable, but increases in Column 3 (-0.099) and Column 4 (-0.091) after fixing its coefficient. This highlights the importance of accounting for the role of spatial and sectoral linkages in estimation. As we will see in the quantitative exercise, nonattainment status increases real wages in attainment counties and decreases real wages in the nonmanufacturing sector, showing how nonattainment's effects spillover through general equilibrium channels. This, combined with the fact that nonattainment status tends to be positively spatially correlated, means our variable of interest $N_{i,t}$ is correlated with the error term. The sign of the bias is ambiguous because the sign of the effect of the general equilibrium spillovers is ambiguous and will depend on fundamentals such as the trade elasticity.

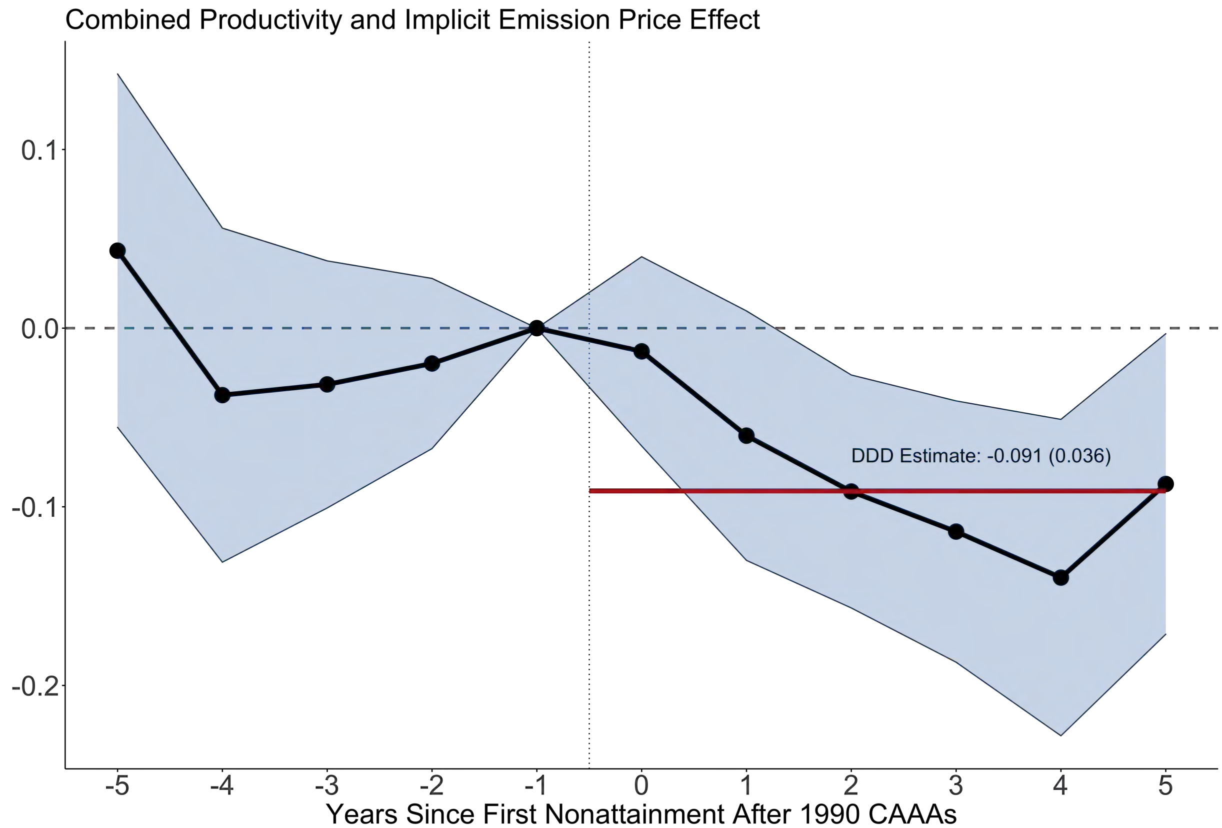
Panel B repeats the same specifications as Panel A but allowing for nonattainment designations for different pollutants to have heterogeneous effects. Here we find that the composite effects are largest for particulate matter and sulfur dioxide nonattainment.

Figure 2 plots the coefficients from event study specifications that correspond on column 4 in Panel A of Table 2. This approach is similar to the approach in Walker (2013) except that we are limited to using variation in nonattainment status across polluting versus non-polluting at the sector level rather than the plant level. The pattern of coefficients is consistent with no effect prior to nonattainment designations after 1990 and then a decrease in industry income that is statistically significant at the 5 percent level following two years f nonattainment.

These results are consistent with previous research on the effect of nonattainment status under the Clean Air Act and its amendments. For example, Greenstone (2002) and Greenstone et al. (2012) use plant-level data and find that that surviving plants experienced productivity losses up to 5 percent, primarily due to standards associated with O_3 and SO_2. In addition, Walker (2013) uses longitudinal data for individual workers and finds earnings losses up to 5 percent. Our approach uses aggregate county- and industry-level data so that we capture both intensive and extensive margin adjustments within a county over time in response to changes in nonattainment status. This may explain our larger estimated effects relative to Greenstone (2002) and Greenstone et al. (2012). Moreover, although we cannot follow workers over time as in Walker (2013), our data covers the entire United States so that combined with our theoretical model we are able to quantify the aggregate effects of environmental regulation.

Combining estimates of $\left(\beta_T - \theta^k \sum_{p=1}^{P} \eta^{kp} \beta_\eta^p\right)$ and β_η^p, we can calculate β_T^k. For simplicity

Figure 2: Event study for the effect of nonattainment on productivity and emissions prices.



Note: The black dots are the point estimates and the blue shaded area is the 95 percent confidence interval derived from robust standard errors clustered at the county level. The event study controls for industry-county, industry-year, and county-year fixed effects. The red line corresponds to the specifications in Table 2 Column 4. The end point estimates are capped: -5 accounts for 5 years greater before nonattainment, while 5 accounts for 5 years and greater after nonattainment.

in the quantitative exercise, and given that counties can be in nonattainment for multiple types of pollutants, we will use the estimate in Panel A and Column 4 in the counterfactuals. Our model will then capture variation in changes in emissions of different kinds of pollutants, but not variation in different kinds of nonattainment designations. To recover β_T^k we first fix θ^k and ξ^{kp} to the calibrated values in Table 3. We use our preferred estimates in Tables 2 and 1 and get $\widehat{\beta_T^k} = -0.050$ which implies nonattainment induces a 5 percent reduction in factor productivity. We jointly bootstrap the estimates of $\left(\beta_T^k - \theta^k \sum_{p=1}^P \eta^{kp}\beta_\eta^p\right)$ and β_η^p at the county level 500 times to compute a nonparametric p-value of 0.096 for our estimate of $\widehat{\beta_T^k}$ indicating that it is statistically significant at the 10 percent level. This estimate of β_T^k, and the estimates of β_η^p in Table 1 Panel B Column 4 are the values we use for our quantitative exercises in the next section.

6 Quantitative Results

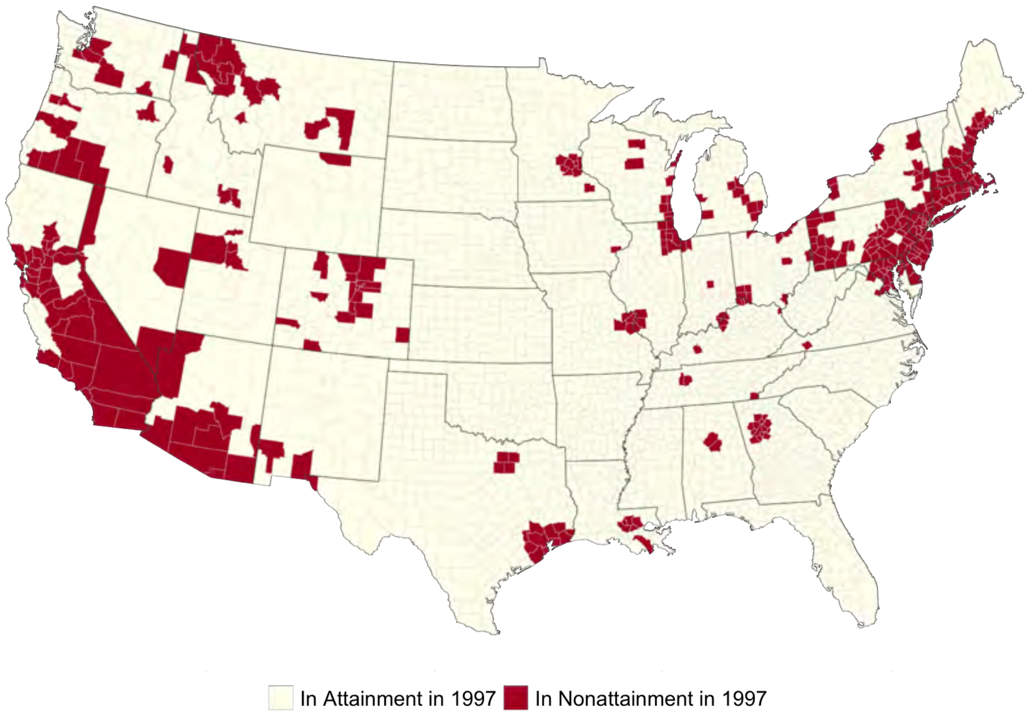
Table 3: Calibrated and estimated parameter values for quantitative model.

Description	**Value**
Consumption Share (α)	0.2740
Labor Share (γ)	0.4810
Trade Elasticity (θ)	4.0000
Pollution Elasticities (ξ^p)	
NH_3	0.0023
NO_x	0.0038
$PM_{2.5}$	0.0023
SO_2	0.0028
VOC	0.0068
Effect of Nonattainment on Emissions Prices (β_η^p)	
NH_3	1.8900
NO_x	0.5230
$PM_{2.5}$	0.2060
SO_2	0.2540
VOC	0.4200
Effect of Nonattainment on Productivity (β_T)	0.0490

Notes: The consumption share comes from Rudik et al. (2021) and is computed using the US World Input Output Database. The labor share comes from Bureau of Labor Statistics (2017). The trade elasticity is from Simonovska and Waugh (2014). The pollution elasticities are drawn from Shapiro and Walker (2018). The effects of nonattainment on emissions prices and productivity are our preferred estimates from Section 5.

With estimates of β_η^p and β_T in hand, we use can the structure of the model to conduct counterfactuals. We use 1997 as our benchmark year and choose the model parameters using

Figure 3: The nonattainment shock to the counterfactual: All counties in nonattainment in 1997.



Note: The figure shows all counties in nonattainment in the benchmark year (in 1997) in red.

estimates from the previous section or values taken from the literature. We summarize these values in Table 3. We consider a baseline counterfactual that compares the equilibrium with the actual set of nonattainment counties in 1997 — shown in Figure 3 — to an equilibrium in which no counties are in nonattainment. We then consider variations of this approach to understand the individual contributions of the productivity and emissions effects as well as the mechanisms underlying spatial and sectoral adjustment.

Table 4 presents the main welfare results. The first column indicates that welfare is 0.49 percent higher under the benchmark scenario relative to the counterfactual scenario with no county in nonattainment. In the second column, this is equivalent to $19.3 billion in annualized terms. The remaining columns show that this total effect can be decomposed into the portion due to the change in amenities and the portion due to the change in real income (or consumption). The total effect is overwhelmingly dominated by the positive effect of nonattainment status on amenities (0.52 percent or $20.6 billion); there is a small negative effect on real income (0.03 percent or $1.2 billion).

We further decompose the aggregate welfare effect by sector and county nonattainment

Table 4: Welfare impacts of nonattainment in 1997.

	Total		Amenity		Consumption	
	%	Billion $	%	Billion $	%	Billion $
Aggregate	*0.49*	*19.3*	*0.52*	*20.6*	*-0.03*	*-1.2*
Manufacturing Sector	0.38	2.1	0.53	2.9	-0.17	-0.9
Nonmanufacturing Sector	0.51	17.1	0.52	17.6	-0.01	-0.3
Attainment Counties	0.21	3.9	0.17	3.2	0.03	0.6
Nonattainment Counties	0.76	15.4	0.86	17.4	-0.09	-1.8

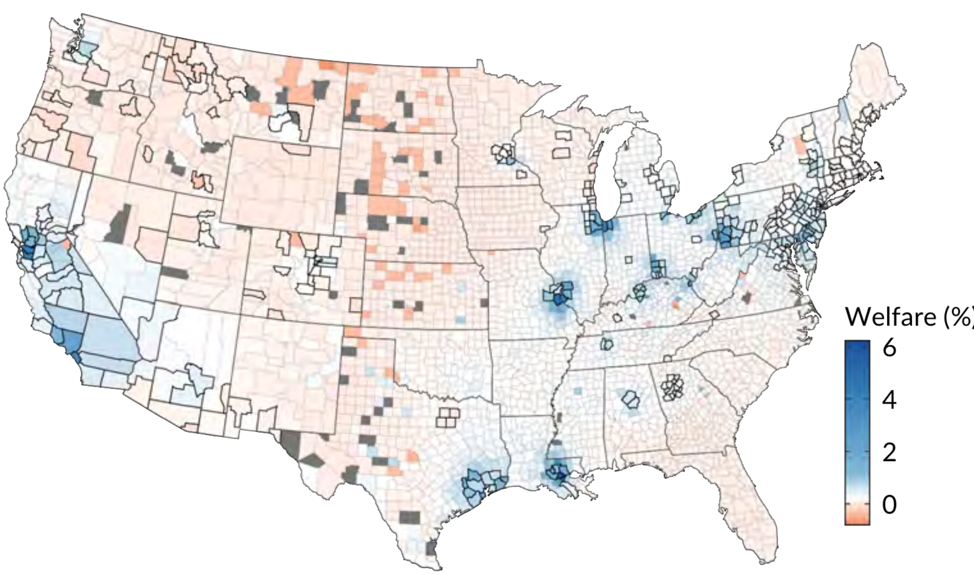
Note: Welfare is computed as the compensating variation of the observed nonattainment statuses in 1997 relative to a counterfactual where no counties are in nonattainment. The simulations account for impacts on emissions, factor productivity, labor reallocation, trade, and atmospheric transport of pollution.

status. The second and third rows of Table 4 show that workers in the polluting sector experience overall welfare gains of 0.38 percent (or $2.1 billion) but that these are smaller relative to gains of 0.51 percent (or $17.1 billion) for workers in the nonpolluting sector. The last two rows of Table 4 indicate that the largest gains accrue to nonattainment counties; nonattainment counties see welfare gains of 0.76 percent (or $15.4 billion) versus gains of 0.21 percent (or $3.9 billion) in attainment counties. In all cases, the positive effect working through improved amenities — rather than gains or losses in real income — accounts the for the largest portion of the overall effect as well as the effects across sectors or nonattainment status.

The map in Figure 4 shows the spatial distribution of the counterfactual change in welfare across all counties in our sample. The areas in darker shades of blue indicate progressively higher gains in contrast with areas that experience losses in red. The map provides an alternative depiction of the previous result in which nonattainment counties see large gains and reveals that there is substantial heterogeneity even within nonattainment counties. Some nonattainment counties, typically in the West, are marginally worse off, while nonattainment counties containing major cities are better off by up to 6 percent. In addition, the map makes clear that counties nearby those in nonattainment in the Rust Belt and South also see substantial welfare improvements. The majority of attainment counties are actually worse off despite their aggregate welfare improvement.

Figure 6 decomposes the welfare results on two margins. The top two maps show the welfare impact on manufacturing and nonmanufacturing. The overall spatial distribution appears similar because improvements in amenities are the largest component of the welfare effect. The primary difference between the two sectors is that manufacturing workers are relatively worse off in nonattainment counties while the opposite is true in attainment

Figure 4: Change in county welfare from nonattainment in 1997.



Note: The change in welfare is the difference between the model with the 1997 nonattainment statuses in effect relative to a counterfactual with no counties in nonattainment. Welfare is in terms of consumption-equivalent compensating variation and can be measured as the equivalent welfare change from a percent change in consumption. Counties outlined in a dark border are those that are in nonattainment in 1997. Grayed-out counties are omitted from the simulations because of missing data. The model includes impacts on productivity and emissions and allows for trade and labor mobility across counties and industries.

counties.

The bottom two maps break down the aggregate welfare impact into amenity improvements and changes in consumption and real wages. The left panel shows that every county has an improvement in amenities. These benefits largely come from the significant decline in emissions in nonattainment counties leading to lower pollution concentrations everywhere. Our model suggests that there is actually a small negative leakage effect as hypothesized in Baylis et al. (2014), where emissions also decline in attainment counties. The idea behind negative leakage is that the increase in the implicit emission price drives nonattainment counties to substitute away from emissions toward labor and capital. This substitution effect increases wages and rental rates in attainment counties (e.g. higher real wages in attainment counties in Table 4), shrinking production and emissions. The map also makes clear that the largest beneficiaries under nonattainment status are getting their welfare improvements almost entirely through improved amenities. The right panel shows the change in welfare caused by changes in real wages and consumption. Consumption declines virtually everywhere outside of California and some areas of the Midwest because a higher implicit emissions price raises the price of manufactured goods and decreases real wages.

Figure 5 shows the reallocation of workers across space. Most nonattainment counties experience a decline in population. The few that have population increases are typically the locations of major cities and experience an influx of nonmanufacturing workers. Workers leaving nonattainment counties are migrating to counties in the plains. This depresses real wages and welfare for incumbent households as shown in Figures 4 and 6.

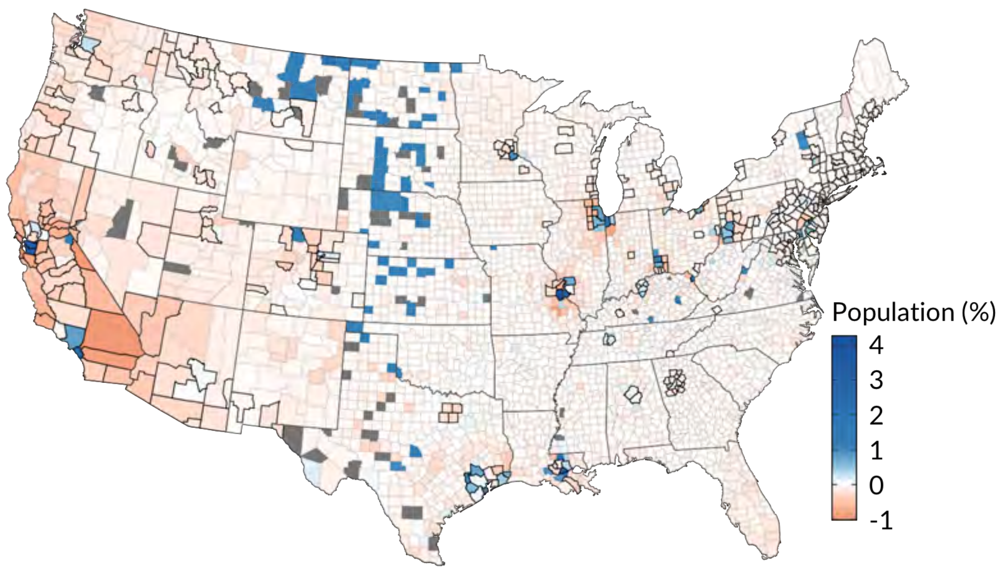
7 Conclusion

In this paper we make two main contributions. First, we develop a theoretical framework in the spirit of Eaton and Kortum (2002). The framework features economic geography forces that govern the spatial distribution of economic activity as well as the potential direct effects on productivity and amenities of a spatial intervention. Second, we use the framework to examine the welfare implications and distributional consequences of the Clean Air Act.

In particular, we estimate the direct costs for firms and workers in polluting sectors from increased regulatory scrutiny and benefits to residents from reduced emissions. We combine these estimates with the full structure of the model to quantify the aggregate impact of nonattainment designations under the Clean Air Act. We find that the Clean Air Act delivers net benefits of \$19.3 billion annually, which substantially reflects the positive effect on amenities (\$20.6 billion) relative to the negative effects on real wages (\$1.2 billion).

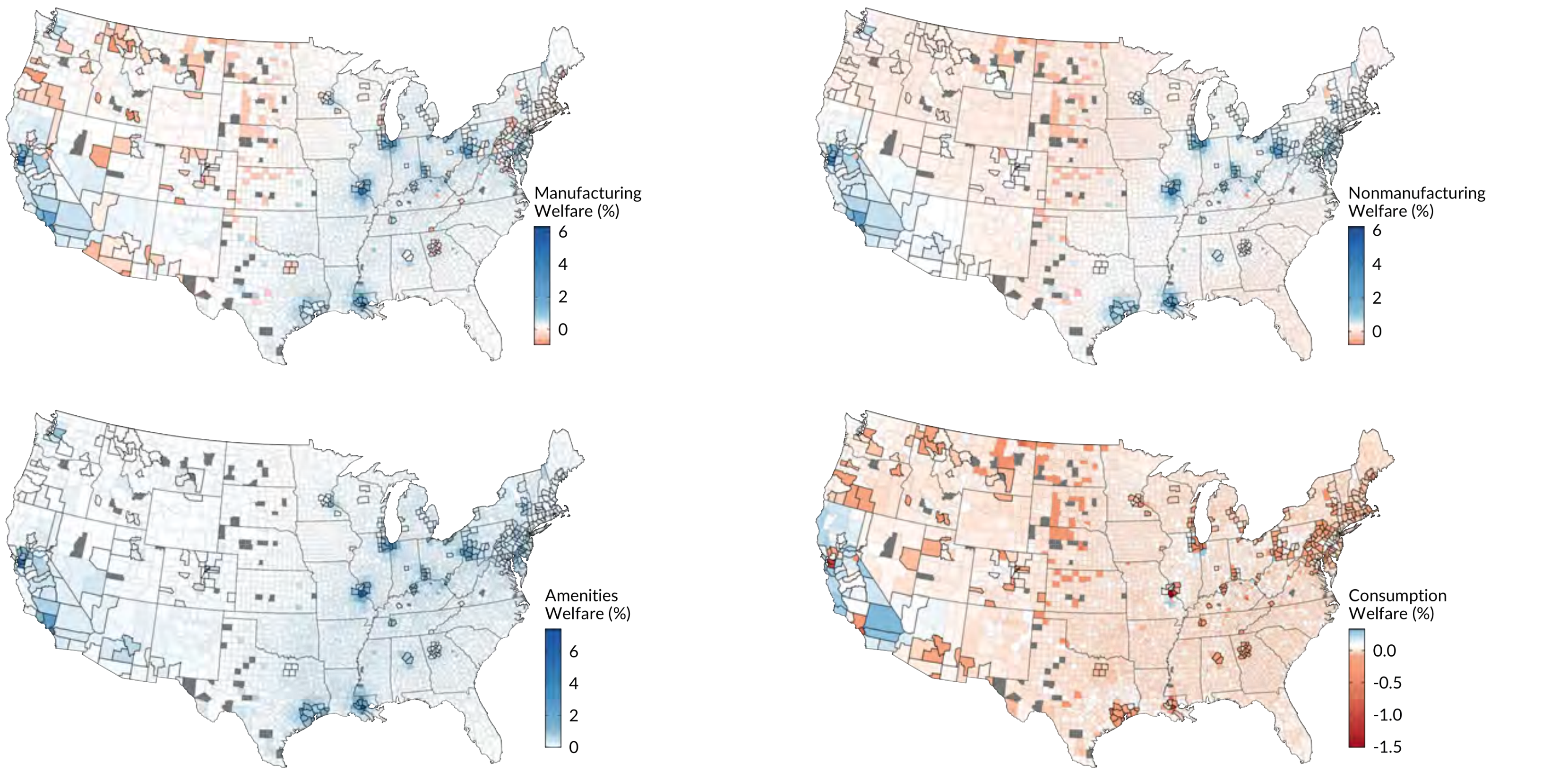
In addition, we use the model to study the mechanisms underlying the spatial distribution

Figure 5: Change in population from nonattainment in 1997.



Note: The change in employment is the percent change in county population under 1997 nonattainment statuses relative to a counterfactual with no counties in nonattainment. Counties outlined in a dark border are those that are in nonattainment in 1997. The model includes impacts on productivity and amenities and allows for trade and labor mobility across counties and industries.

Figure 6: Change in manufacturing, nonmanufacturing, amenities, and consumption welfare from nonattainment in 1997.



Note: The change in welfare is the difference between the model with the 1997 nonattainment statuses in effect relative to a counterfactual with no counties in nonattainment. Welfare is in terms of consumption-equivalent compensating variation and can be measured as the equivalent welfare change from a percent change in consumption. Counties outlined in a dark border are those that are in nonattainment in 1997. Grayed-out counties are omitted from the simulations because of missing data. The model includes impacts on productivity and emissions and allows for trade and labor mobility across counties and industries.

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of these effects. Specifically, workers are imperfectly mobile across sectors and locations, the spread of emissions is affected atmospheric transport, and interregional trade is subject to iceberg trade costs. All of these factors potentially shape adjustments in response to changes in environmental regulation. We find that atmospheric pollution transport is particularly important in our setting.

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A Appendix

A Amenities in Reduced Form

In the quantitative model we structurally model the relationship between nonattainment, emissions, and the spatial transport of pollution. The model assumes that households have perfect information and reallocate across space in response to changes in the spatial distribution of pollution. To validate this assumption and to gauge the size of our model estimates of welfare impacts through amenities, we estimate a reduced form relationship between nonattainment and amenities using the households' spatial equilibrium conditions.

In general, we can represent B_i as:

$$B_i = \bar{B}_i \exp\left(\beta_B N_{i,t}\right). \tag{14}$$

$\bar{B}_i$ is the county's baseline level of amenities, and $\exp\left(\beta_B N_{i,t}\right)$ captures how nonattainment status N_i affects local amenities. $\exp\left(h(N_i;\beta_{\mathbf{B}})\right)$ is a function of the county's nonattainment status N_i which is an indicator variable $N_i = \{0,1\}$. h is also linear in a vector of parameters $\beta_{\mathbf{B}}$ that will we estimate and can be interpreted as the percent change in amenity-related welfare from imposing nonattainment status.

We obtain our equation of interest by manipulating equation (1) to obtain an expression for the log share of workers who migrate to j relative to those who stay in i $\log(\pi_{ij}/\pi_{ii})$:

$$\log\left(\frac{\pi_{ij}}{\pi_{ii}}\right) = \log\left(\frac{V_j B_j \delta_{ij}}{V_i B_i \delta_{ii}}\right) = \log\left(\frac{w_j/P_j}{w_i/P_i}\right) + \log(\delta_{ij}) + \log(\bar{B}_j/\bar{B}_i) + \beta_B\left(N_j - N_i\right)$$

where $\delta_{ii} = 1$. We drop industry superscripts because we do not observe industry of employment in the county-to-county migration data. Next, rearrange this expression to obtain an equation with data on the left hand side as a function of parameters to estimate and capture with fixed effects:

$$\log\left(\frac{\pi_{ij}}{\pi_{ii}}\right) = \beta_B\left(N_j - N_i\right) + \log(\bar{B}_j/\bar{B}_i) + \log\left(\frac{w_j/P_j}{w_i/P_i}\right) + \log(\delta_{ij}). \tag{15}$$

The difference in the share of people in i who migrate to j relative to those who stay in i is equal to the difference in amenities, differences in real wages, and migration costs.

Amenities are common across workers in both industries so we use a difference-in-differences approach:

$$\log\left(\frac{\pi_{ij,t}}{\pi_{ii,t}}\right) = \beta_B\left(N_{j,t} - N_{i,t}\right) + \log\left(\frac{w_j/P_j}{w_i/P_i}\right) + \phi_{ij} + \nu_t + \varepsilon_{ij,t} \tag{16}$$

where migration costs are absorbed by the origin-destination fixed effect ϕ_{ij} and $\varepsilon_{ij,t}$ is the error term. Standard errors are clustered two ways at the origin and destination counties.

This reduced form estimate of nonattainment's effects on amenities provides two important benefits. First, the estimate is identified off of variation in migration flows and quasi-experimental regulatory variation. If our model assumption that households observe and respond to pollution is incorrect, it will show up as a zero estimate here. Second, this approach allows us to be agnostic about the precise ways in which nonattainment status can induce improvements in amenities. In addition to reductions in air emissions reducing mortality, there may be other benefits not captured in our structural model such as reductions in noise, or improved foliage from better air quality. This, along with the fact that we are not capturing all pollutants, suggests that the reduced form impact on amenities should exceed the model-based estimates and gives us another sanity check on our model.

A.1 The Effect of Nonattainment on Amenities

Table A1 shows the results from estimating models building up to our preferred specification in equation (16). Column 1 presents results with origin-by-destination and year fixed effects, the real wage control omitted, and forcing the coefficients on origin nonattainment status and destination nonattainment status to be identical. Column 1 suggests that nonattainment status improves local amenities such that, on average, utility increases by 4.0 percent in consumption-equivalent terms. Column 2 adds in the real wage control, Column 3 fixes the coefficient on real wages to equal 1 to be consistent with the model, and Column 4 further allows nonattainment status to have differential effects depending on whether its the origin or destination county. All specifications generate estimates that nonattainment status improves utility by 3–4 percent.

Table A1: Difference-in-differences estimates of the effect of nonattainment on local amenities.

	(1)	(2)	(3)	(4)
1(Dest. Nonattainment) - 1(Orig. Nonattainment)	0.040***	0.040***	0.034***	
	(0.013)	(0.013)	(0.013)	
1(Destination Nonattainment)				0.034***
				(0.013)
1(Origin Nonattainment)				−0.033***
				(0.013)
Observations	704506	704506	704506	704506
Origin-Destination FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Real Wage	Omitted	Coef. Free	Coef. Fixed	Coef. Fixed
Origin vs Destination	Fixed	Fixed	Fixed	Free

Robust standard errors are clustered two ways at the origin county and destination county levels.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Figure A1 shows the results corresponding to Table A1 Column 3. Since the IRS cross-county migration data begins in 1990, we have a limited set of pre-periods. Only 60 observations total identify pre-periods before -2, whereas every other period has at least 1,000 observations each. Given this data limitation, we cap the pre-periods at -2. Prior to going into nonattainment after the 1990 CAAAs, counties had, if anything, worsening amenities. Post-nonattainment, amenities generally improved: the three largest point estimates are in the post-period, and all post-period estimates are positive relative to the year prior to first nonattainment after the 1990 CAAAs.

A.2 Simulating Counterfactuals

To simulate our counterfactual we need to solve for the level of productivity T_i^k and the implicit price of emissions η_i^{kp}. We will not need to solve for the level of amenities B_i since observed migration shares are effectively sufficient statistics for the composition of moving costs and differences in base amenities across locations.[16]

First we solve for the baseline emission price. To recover η_i^{kp} we use the equilibrium condition for emissions intensity in equation (2) and recognizing that with Cobb-Douglas technology, labor is paid a fixed share: $w_i^k L_i^k = \gamma \left(1 - \sum_{q=1}^{P} \xi^{kq}\right) Y_i^k$ to obtain:

$$\eta_i^{kp} = \frac{\xi^{kp}}{\gamma \left(1 - \sum_{q=1}^{P} \xi^{kq}\right)} \frac{w_i^k L_i^k}{e_i^k}$$

where w_i^k, L_i^k, and e_i^k are data and the remaining variables are calibrated constants. This allows us to identify the implicit price on emissions.

Next we solve for baseline productivity. Combining equations (6) and (9) we have that:

$$Y_i^k = T_i^k (c_i^k)^{-\theta} \sum_{j=1}^{N} \frac{\tau_{ji}^{-\theta^k} Y_j^k}{CMA_j^k} \tag{17}$$

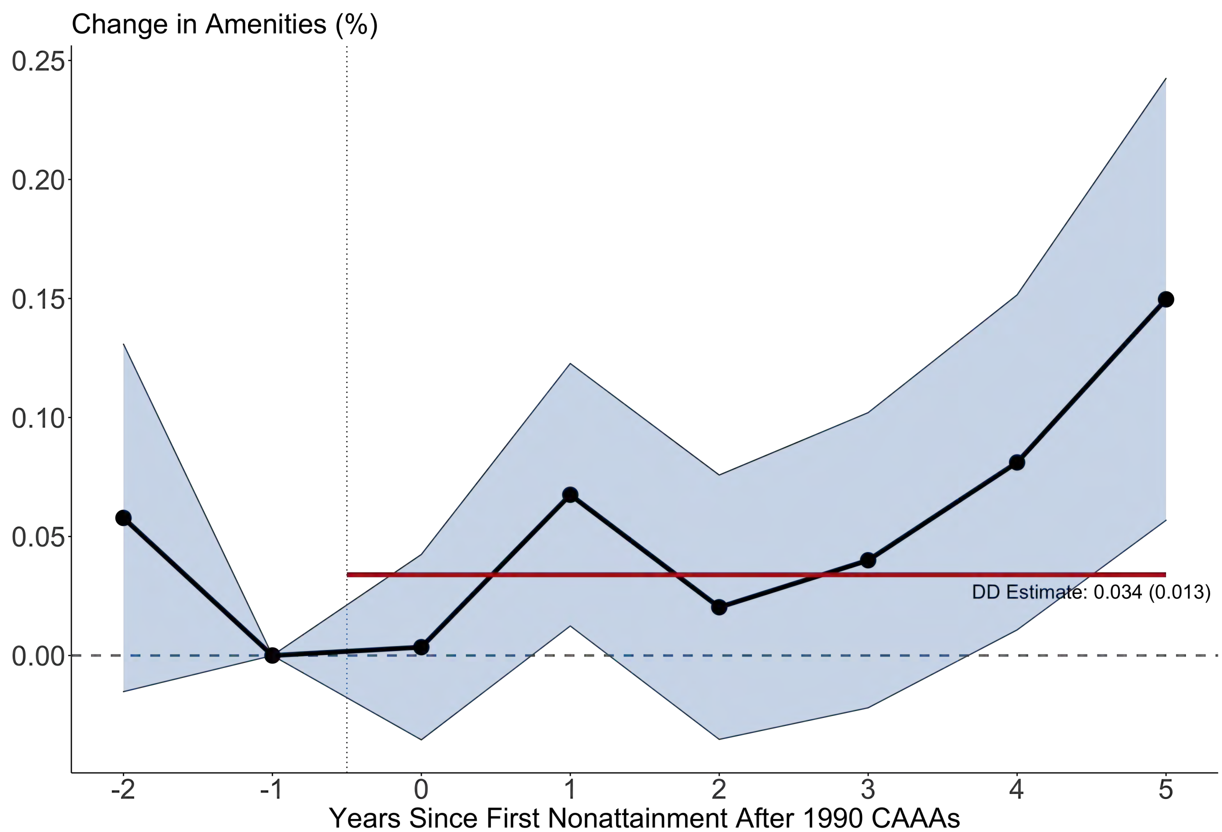
Next define firm market access as:

$$FMA_i^k = \sum_{j=1}^{N} \frac{\tau_{ji}^{-\theta^k} Y_j^k}{CMA_j^k} \tag{18}$$

The two market access terms are equivalent up to a normalization so we define market access

[16] If we observed county-level trade flows we could simulate counterfactuals without solving for T_i as they are effectively sufficient statistics for productivity.

Figure A1: Difference-in-differences event study estimates of effects of nonattainment on local amenities using quasi-experimental variation from the 1990 CAAAs.



The plot is the event study analogue of Table A1 Column 4. The black dots are the point estimates and the blue shaded area is the 95 percent confidence interval derived from robust standard errors clustered two ways at the origin and destination levels. Event times -2 and 5 are capped. The red line corresponds to the average of origin and destination estimates in the specification in Table A1 Column 4.

MA_i^k as:[17]

$$MA_i^k \equiv FMA_i^k = \rho CMA_i^k.$$

We can manipulate equation (17) and obtain a system of equations that characterize the equilibrium labor allocation:

$$T_i^k = \rho_1 \frac{L_i^k \left[w_i^k\right]^{\left((1+\theta^k \gamma\left(1-\sum_{q=1}^P \xi^{kq}\right)\right)} \prod_{q=1}^P (\eta_i^{kq})^{-\xi^{kq}\theta^k}}{MA_i^k} \tag{19}$$

where we previously solved for η_i^{kp}, w_i^k and L_i^k are data, and ρ_1 is a constant.

In equation (19) we have $N \times K$ endogenous market access variables MA_i^k and $N \times K$ productivity parameters T_i^k that we need to identify. First, we can identify the MA_i^k terms. Substituting MA_i^k into equation (18) for FMA_i^k and CMA_i^k, and that $Y_i^k = \frac{w_i^k L_i^k}{\gamma\left(1-\sum_{q=1}^P \xi^{kq}\right)}$ gives us:

$$MA_i^k = \rho_2 \sum_{j=1}^N \tau_{ji}^{-\theta^k} \left(MA_j^k\right)^{-1} w_j^k L_j^k \tag{20}$$

where w_j^k, L_j^k, and τ_{ji} are data and ρ_2 is a constant. We iterate on equation (20) to solve for the factual MA_i^k up to a normalization. Next we insert the recovered MA_i^k terms into equation (19) and use the observed data on labor, wages, and nonattainment status to recover T_i^k.

Now that we have η_i^{kp} and T_i^k, we can simulate counterfactual outcomes given a change in nonattainment from N_i to N_i' where primes denote counterfactual variables. The counterfactual levels of emissions prices and productivity are given by: $\eta_i^{kp\prime} = \eta_i^{kp} \exp(\beta_\eta(N_i' - N_i))$ $T_i^{k\prime} = T_i^k \exp(\beta_N(N_i' - N_i))$.

Our model has $(N \times K)^2 + 3(N \times K)$ endogenous variables: π_{ij}', $MA_i^{k\prime}$, $L_i^{k\prime}$, $w_i^{k\prime}$ so we require at least these many equations to solve counterfactuals. We do so using four equilibrium conditions of the model. The first two are equations (19) and (20) along with the identity that $P_i^{k\prime} = (MA_i^{k\prime})^{-1/\theta^k}$ This pins down $2(N \times K)$ variables. The remaining $(N \times K)^2 + N \times K$ variables are pinned down by how migration and thus the labor distribution responds to the

[17]For example see, Anderson and Van Wincoop (2003) or Donaldson and Hornbeck (2016).

counterfactual change in amenities $N_j' - N_j$:[18]

$$\pi_{ij}^{km\prime} = \frac{\frac{\frac{w_j^{m\prime}}{P_j'}B_j'}{\frac{w_j^m}{P_j}B_j}\pi_{ij}^{km}}{\sum_{l=1}^K\sum_{n=1}^N \frac{\frac{w_n^{l\prime}}{P_n'}B_n'}{\frac{w_n^l}{P_n}B_n}\pi_{in}^{kl}} = \frac{\frac{\frac{w_j^{m\prime}}{P_j'}}{\frac{w_j^m}{P_j}}\pi_{ij}^{km}\exp(\beta_B(N_j'-N_j))}{\sum_{l=1}^K\sum_{n=1}^N \frac{\frac{w_n^{l\prime}}{P_n'}}{\frac{w_n^l}{P_n}}\pi_{in}^{kl}\exp(\beta_B(N_n'-N_n))} \tag{21}$$

$$L_i^{k\prime} = \sum_{l=1}^K\sum_{n=1}^N \pi_{ni}^{lk\prime}L_n^{l\,\prime} \tag{22}$$

where the second equality assumes that the only component of amenities that is different in the counterfactual is nonattainment status. With these $(N\times K)^2 + 3(N\times K)$ equilibrium conditions, we can then solve for the set of endogenous variables given any counterfactual set of nonattainment designations across counties.

B Welfare Derivation

Recall that indirect utility from consumption and amenities is given by $V_i = \frac{w_i}{P_i}B_i$ and that migration shares are governed by $\pi_{ij} = \frac{V_j\delta_{ij}}{\sum_{k=1}^N V_k\delta_{ik}}$. Rearrange and take the log of the expression for own-migration shares to get:

$$-\log\pi_{ii} = \log\left[\sum_{k=1}^N \frac{V_k}{V_i}\bar{\delta}_{ik}\right]. \tag{23}$$

Let W_i be the expected total welfare for a household in location i net of moving costs. The assumption that ϵ_{ij} is Type 1 Extreme Value gives us that:

$$W_i = \log\left[\sum_{k=1}^N V_k\bar{\delta}_{ik}\right]$$

which is a function of unobserved moving costs. Next rearrange equation (23) and solve for W_i:

$$W_i = \log\left(\frac{w_i}{P_i}B_i\right) - \log\mu_{ii}.$$

[18]For amenities and migration must we difference nonattainment status because we are not able to recover the level of amenities like we were for productivity. Assuming amenities are otherwise constant between the factual and counterfactual, the change in amenities is given by the difference in nonattainment status.

Table A2: Difference-in-differences estimates of the effect of nonattainment on the implicit emissions price varying the sample period.

	(1)	(2)	(3)	(4)	(5)	(6)
β^p_η	0.35**	0.34**	0.34**	0.36**	0.37**	0.37**
	(0.14)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
Observations	19005	28940	38890	49245	59610	70225
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No
Pollutant FE	No	No	No	No	No	No
Pollutant-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Latest Year	1996	1997	1998	1999	2000	2001

Robust standard errors are clustered at the county level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Define the compensating variation at some location i to be χ_i where:

$$W_i' = W_i + \log \chi_i$$

and primes indicate a counterfactual quantity. Let $\widehat{x} := x'/x$ for some variable x. The consumption-equivalent change in welfare under some counterfactual is then given by $\log \chi_i$:

$$\log \chi_i = \widehat{W}_i = \log \left(\frac{\widehat{w}_i}{\widehat{P}_i} \widehat{B}_i \right) - \log \widehat{\mu}_{ii}.$$

C Robustness Checks

Sample Periods Tables A2 and A3 present robustness checks of our main results (Panel A in both tables) with respect to the sample period. For emissions we only have one pre-period so we can only change the post-period sample. Our estimates are highly robust to the chosen years of inclusion.

Table A3: Triple difference estimates of the effect of nonattainment on a combination of factor productivity and implicit emissions prices varying the sample period.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\beta_T - \theta^k \sum_{p=1}^{P} \eta^{kp} \beta_\eta^p$	-0.106**	-0.104**	-0.104***	-0.114***	-0.108**	-0.091**	-0.096**	-0.095**
	(0.044)	(0.043)	(0.040)	(0.040)	(0.047)	(0.043)	(0.044)	(0.046)
Num.Obs.	60296	54307	48312	42300	60232	54178	48142	42098
Industry-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nonattainment-Year FE	No	No	No	No	No	No	No	No
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Earliest Year	1988	1989	1990	1991	1986	1986	1986	1986
Latest Year	1997	1997	1997	1997	1996	1995	1994	1993

Robust standard errors are clustered at the county level.

* p < 0.1, ** p < 0.05, *** p < 0.01

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Table A4: Triple difference estimates of the effect of nonattainment on a combination of factor productivity and implicit emissions prices varying the real wage coefficient.

	(1)	(2)	(3)	(4)	(5)	(6)
$\beta_T - \theta^k \sum_{p=1}^{P} \eta^{kp} \beta_\eta^p$	−0.105*	−0.084***	−0.105*	−0.084***	−0.091**	−0.091**
	(0.055)	(0.027)	(0.055)	(0.027)	(0.036)	(0.036)
Observations	72279	72279	72279	72279	72279	72279
Industry-County FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Nonattainment-Year FE	No	No	No	No	No	No
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Labor Share	.962	.241	.481	.481	.481	.481
Trade Elasticity	4	4	8	2	4	4
Sum of Pollution Elasticities	.018	.018	.018	.018	.036	.009

Robust standard errors are clustered at the county level.
* p < 0.1, ** p < 0.05, *** p < 0.01

Alternative Trade and Pollution Elasticities Our preferred estimate of $\left(\beta_T - \theta^k \sum_{p=1}^{P} \eta^{kp} \beta_\eta^p\right)$ from equation (13) fixed the coefficient on the real wage control variable, which depends on the value of the labor share γ, the trade elasticity θ, and the pollution elasticities ξ^{kp}. Table A4 re-estimates our preferred specification with higher and lower values of each of the three sets of parameters. Our preferred estimates are largely insensitive to these choices.

Alternative Quantitative Parameters Table A5 reports the total welfare effects of the nonattainment counterfactual scenario but under different calibrated parameter values. The first row reports the base welfare outcomes in the main text. The second two rows vary the trade elasticity and show that the quantitative values are sensitive to it, but the qualitative takeaways remain the same. The next four rows vary the consumption share parameter and the labor share parameter. The quantitative results are insensitive to their values. The last row introduces congestion externalities so that amenities can be written as:

$$\tilde{B}_i = B_i L_i^{\zeta}$$

where B_i is amenities without congestion, and ζ is the congestion elasticity and equal to -0.3 following Allen and Arkolakis (2014). The existence of congestion slightly raises the benefits of nonattainment because it induces households to migrate away from denser counties.

Table A5: Welfare impacts of nonattainment in 1997 under different model parameter values.

Parameter Change	Total %	Manuf. %	Nonmanuf. %	Attain. %	Nonattain. %
Base Parameters	*0.49*	*0.38*	*0.51*	*0.2*	*0.76*
$\theta = 8$	0.33	0.45	0.31	0.1	0.55
$\theta = 2$	1.4	1.09	1.45	0.78	1.97
$\alpha = 0.548$	0.49	0.38	0.51	0.21	0.76
$\alpha = 0.137$	0.49	0.38	0.51	0.2	0.76
$\gamma = 1$	0.49	0.41	0.5	0.18	0.79
$\gamma = 0.2405$	0.49	0.36	0.51	0.24	0.72
Congestion Elasticity = -0.3	0.51	0.4	0.53	0.21	0.78

Note:
Welfare is computed as the compensating variation of the observed nonattainment statuses in 1997 relative to a counterfactual where no counties are in nonattainment. The simulations account for impacts on emissions, factor productivity, labor reallocation, trade, and atmospheric transport of pollution.

D Supporting Results

Effects on Manufacturing Employment To provide further evidence of nonattainment-induced reallocation, Table A6 uses a difference-in-differences strategy to estimate the effect of nonattainment on log employment and the share of county employment in manufacturing. We find evidence that nonattainment reduces the level of manufacturing employment, and manufacturing relative to nonmanufacturing, indicating a reallocation of workers away from the regulated sector.

Welfare Value of Reallocation Figure A2 plots the welfare value of reallocation. The left map shows the value of labor reallocation, and the right map shows the value of reallocation through trade (i.e. changing market access). The aggregate effect of both is small but the left map shows that there is significant amounts of heterogeneity in the county-specific value of labor reallocation: some counties gain by nearly a quarter of a percent, while some counties lose by over 2 percent. The right map shows that there is very little heterogeneity for reallocation through trade.

Figure A3 plots the change in welfare through congestion. The estimates are the direct welfare values of the population changes in Figure 5.

Table A6: Difference-in-differences estimates of the effect of nonattainment on log manufacturing employment and the share of county-year employment in manufacturing.

	log(Manufacturing Emp.)		Manufacturing Emp. / Total Emp.	
	(1)	(2)	(3)	(4)
1(Nonattainment)	−0.049*	−0.010	−0.010***	−0.006*
	(0.029)	(0.028)	(0.003)	(0.003)
Observations	36660	36660	36642	36642
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Market Access Control	No	Yes	No	Yes

Robust standard errors are clustered at the county level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A2: Value of labor reallocation and trade.

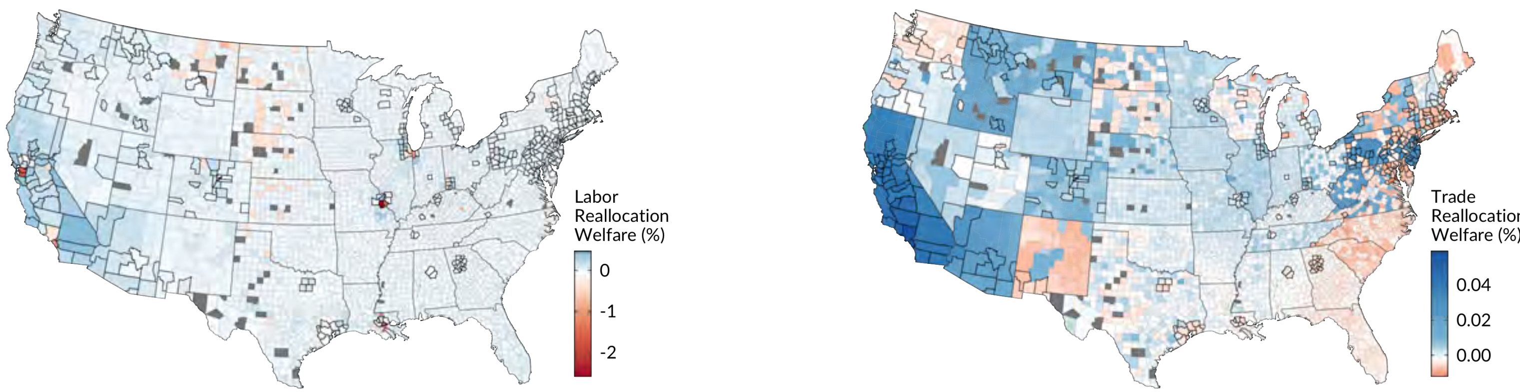

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Figure A3: Value of congestion.