Economic Geography and Air Pollution Regulation in the United States*

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Abstract

We develop a quantitative economic geography model with endogenous emissions, amenities, trade, and labor reallocation to evaluate the spatial impacts of the leading air quality regulation in the United States: the National Ambient Air Quality Standards (NAAQS). We find that the NAAQS generate over $50 billion in annual welfare gains. The gains are spatially concentrated in a small set of cities targeted by the NAAQS, and the improved amenities attract large numbers of nonmanufacturing workers into these areas. Despite the concentration of the benefits in cities, over $10 billion in benefits spill over into counties indirectly affected by the regulation. We use our model to analyze counterfactual policies and find that making the NAAQS more stringent could have increased welfare by another $13 billion annually, and that using emissions pricing could increase welfare by another $70 billion per year.

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1 Introduction

In the last several decades, governments around the world have enacted regulations intended to improve environmental quality. These environmental protections directly benefit individuals through improved health, recreation, and other channels. However, more stringent regulation of polluting activities may impose substantial costs on firms and workers. Understanding the total impact of these policies is difficult since it requires information on abatement costs and damages together with a model that captures equilibrium responses, the physical geography of pollutants, and heterogeneity across sectors and locations.

In this paper, we develop a novel quantitative economic geography model to overcome these challenges. Our model couples an Eaton and Kortum (2002)-based spatial equilibrium model with a benchmark integrated assessment model for air pollution (Mendelsohn and Muller, 2013).[1] The model captures goods traded across locations, labor that is imperfectly mobile across space and between sectors, endogenous emissions of local air pollutants, and non-uniform atmospheric transport of local air pollutants. Greater local air pollution increases local mortality risk which is captured in our model as a reduction in local amenities.

We use our model to study the equilibrium impacts of the primary air quality regulation in the United States: the National Ambient Air Quality Standards (NAAQS) under the Clean Air Act (CAA). The NAAQS are a set of standards for ambient concentrations of six criteria pollutants. If criteria air pollution concentrations within a county exceed any of these standards, the county is out of compliance and designated as in "nonattainment." Polluting plants in nonattainment counties must adopt costly abatement technologies and comply with other burdensome requirements. In our model, emissions are a function of nonattainment status to capture the link between environmental regulation, the incentive to reduce emissions, and firm costs. In this way, we are able to map the regulation-induced changes in emissions to changes in local ambient pollution and local amenities across all counties in the United States, while also accounting for responses to environmental regulation that drive further endogenous changes in emissions, amenities, and prices.

To take the model to the data, we estimate how the NAAQS affect firm emissions with quasi-experimental variation in county-level nonattainment status due to changes under the 1990 CAA amendments. The 1990 CAA amendments increased regulatory scrutiny and costs

[1] Holland, Mansur, Muller and Yates (2016) and Holland, Mansur, Muller and Yates (2019) use the same air quality integrated assessment model to estimate impacts of electric vehicle adoption and second-best policy design, Muller and Mendelsohn (2009) and Tschofen, Azevedo and Muller (2019) use it to do environmental economic accounting and to measure mortality damages, while Clay, Jha, Muller and Walsh (2019) uses it to measure external costs of shipping oil. Our contribution is to combine this same integrated assessment model with a quantitative spatial equilibrium model that covers the entire economy and allows for fully endogenous pollution responses.

to polluting firms by introducing 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 designations. This led to the largest change in nonattainment since 1978 (Walker, 2013).[2] We estimate the impact of nonattainment designations on the implicit marginal cost (i.e., shadow price) that firms face for emissions by comparing emissions intensities before versus after the new nonattainment designations, in nonattainment versus attainment counties. We find that the implicit marginal cost of emitting the five pollutants captured by our model increases by an average of 60 percent, but with significant heterogeneity.

We then use our quantitative model and the empirical estimates to consider counterfactual outcomes that would have occurred if counties had never gone into nonattainment.[3] We compute changes in welfare, employment, and population outcomes under the actual nonattainment designations relative to a counterfactual scenario in which no county was in nonattainment. The results imply nonattainment designations led to a 0.91 percent increase in welfare from improved amenities through lower fine particulate concentrations, and a 0.08 percent decrease from lower real wages driven by higher prices and lower nominal wages. Overall, welfare increased by 0.82 percent or $57 billion per year. In present value terms at a 3 percent discount rate, total benefits are nearly $2 trillion. We then study counterfactual policies to see whether welfare could be improved even further. We find that adopting the 2022 NAAQS 25 years earlier would have improved welfare by another 0.14 percent or $6 billion per year, and that adopting the first-best location-differentiated emission price policy would more than double the gains to over $120 billion per year.

To understand the forces driving these results, we decompose the effects across sectors and regions. In the aggregate, workers in the polluting and nonpolluting sectors are better off, but to different degrees. Workers in the polluting sector in our setting – manufacturing – suffer real wage losses of 0.42 percent, offsetting about three-quarters of the value of their amenities improvements. Workers in the nonpolluting sector – nonmanufacturing – only have real wages losses of 0.05 percent, giving them greater welfare improvements. Welfare gains are also highly unequal across space. They mostly accrue to several high-population, urban counties and other counties nearby. In dollar terms, only 15 counties account for half of the aggregate welfare gains.

Finally, we quantify the mechanisms that shape the margins of adjustment. In response

[2]Reduced form evidence has shown that nonattainment designation makes it more costly for polluting firms to enter, induces exit of incumbent firms, and negatively affects the polluting sectors' workforce, output, and productivity (Henderson, 1996; Becker and Henderson, 2000; Greenstone, 2002; Walker, 2013).

[3]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.

to the effects of nonattainment, labor reallocates across space and sectors. Reallocation has a positive effect on real wages as suggested by standard economic theory and previous work (Andersen, 2018), but the effects are highly heterogeneous across workers. Migration allows workers in the nonpolluting sector to move into nonattainment counties and benefit from the improved air quality, while migration allows workers in the polluting sector to move out of nonattainment counties to places that will pay higher wages. The results also show that nonattainment designations reduced emissions in attainment counties through general equilibrium channels, a phenomenon hypothesized by the theoretical literature (Baylis, Fullerton and Karney, 2014). These findings highlight the importance of accounting for both economic and physical processes when designing and evaluating environmental policy.

Our paper contributes to three main areas of research. First, our paper is related to recent work using economic geography models to examine the economic impacts of environmental change (Hanlon, 2020; Balboni, 2021; Heblich, Trew and Zylberberg, 2021; Cruz and Rossi-Hansberg, 2021; Nath, 2021; Rudik, Lyn, Tan and Ortiz-Bobea, 2021). We add to this literature by studying environmental regulation and its impact on the environment by combining a benchmark economic geography model with a workhorse air pollution integrated assessment model. Coupling the two models allows us to capture firms' endogenous changes in emissions, and how this translates into spatially heterogeneous changes in local amenities. In this way, our work is most closely related to Aldeco, Barrage and Turner (2019), who study the global impact of particulate emissions and the equilibrium efficacy of policy responses. Our finding that welfare gains are highly concentrated in a small set of major cities further highlights the role of environmental regulation in improving urban amenities, and the revitalization of American cities in the last few decades (Kahn and Walsh, 2015; Baum-Snow and Hartley, 2020; Couture and Handbury, 2020).

Second, we contribute to the empirical literature on the impact of environmental regulation and, more specifically, the Clean Air Act. One part of this literature focuses on estimating the effect of nonattainment designations under the NAAQS. On the one hand, 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). On the other hand, several papers document negative effects: on firms due to higher costs and reduced competitiveness; on workers through lower wages, and increased rates of nonemployment and costly job transitions (Becker and Henderson, 2000; Greenstone, 2002; Greenstone et al., 2012; Walker, 2013).[4] Our paper bridges these parts of the literature. We develop a nationwide

[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). In the

economic geography model that accounts for direct costs and benefits of the NAAQS, but also how households adjust in response to improved amenities and depressed wages through costly migration or changing sectoral employment. This allows us to perform one of the most comprehensive, spatially detailed, and internally consistent analyses of the NAAQS.

Finally, we contribute to research emphasizing the role of general equilibrium responses to environmental policies. This literature examines the efficiency and incidence of different types of policies, mostly in stylized settings (Bovenberg and Goulder, 1996; Goulder, Parry, Williams III and Burtraw, 1999; Fullerton and Heutel, 2007; Bento, Goulder, Jacobsen and Von Haefen, 2009; Fullerton and Heutel, 2010, 2011; Goulder, Hafstead and Williams III, 2016; Hafstead and Williams III, 2018). Our paper is closely related to the work by Shapiro and Walker (2018), which uses a quantitative trade model to show that environmental regulation has been the primary cause of the large decline in emissions from US manufacturing over the last several decades.[5] We complement this work by analyzing the spatial impacts of the primary air pollution regulation in the United States and its associated emissions reductions, and also leveraging the structure of the model to study counterfactual policies.

The remainder of this paper is organized as follows. The next section provides 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 emissions. Section 6 presents the counterfactual results. Section 7 concludes.

2 Institutional Setting

Originally passed in 1963, the Clean Air Act established several 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 to 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

appendix we use a similar approach to validate the structure and results of our quantitative model using cross-county migration flows.

[5]Earlier empirical work showed that reductions in emissions intensity of manufacturing output, rather than changes in sectoral scale or composition, were responsible for the vast majority of pollution declines (Levinson, 2015). In addition, Sieg et al. (2004) examine household willingness to pay for ozone reductions in Southern California and find that using a general equilibrium rather than partial equilibrium analysis affects the distribution of benefits across households.

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 amendments. States were mandated to regulate plant-level sources of pollutants in counties found to be in nonattainment – that is, those counties that violated the standards set for any particular pollutant.

The 1977 amendments introduced additional regulations. Following a county's nonattainment designation, a state is required to create a state implementation plan (SIP) outlining how it will bring that county 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 amendments limit entry of new pollution sources in nonattainment areas and impose costs on existing pollution sources. Any new or modified source of criteria pollution is mandated to be at the lowest achievable emissions rate (LAER) in nonattainment counties; by contrast, new or modified sources in attainment counties are required to use only the best available control technology (BACT). Existing plants in nonattainment counties must adopt a Reasonably Available Control Technology (RACT). Despite the absence of uniform standards for these technologies, LAER is generally acknowledged to be 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 leads to movement of plants to counties that were historically in attainment (Henderson, 1996; Becker and Henderson, 2000), providing evidence for spatial 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). We exploit variation in nonattainment status due to the heightened regulatory scrutiny following the passage of these amendments and their subsequent enforcement (Grainger, 2012; Walker, 2013; Bento et al., 2015). 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). We take this timing into account in our empirical analysis.

3 Model

We develop a Ricardian model of interregional trade for the United States in the spirit of Eaton and Kortum (2002).[6] In the model there are N locations indexed by i, j, n and K sectors indexed by k, l, m. When quantifying the model we use the approximately 3,000 US counties as locations and use two sectors, polluting and nonpolluting, defined in Section 4.3 below. In addition, we allow for nonemployment to capture potential permanent transitions out of work. Firms use labor and capital as inputs into production. Production generates emissions – or isomorphically, emissions are an input to production (Copeland and Taylor, 2013). Emissions are not traded in markets, but firms face an implicit marginal cost of emissions imposed by the prevailing set of local environmental regulations such as the NAAQS. Labor is imperfectly mobile across locations and sectors, while capital is perfectly mobile so that the rental rate is equalized across locations.

Differences in implicit emissions prices across counties and sectors affect the allocation of labor and emissions and, hence, the spatial and sectoral distribution of economic activity. In our model, we incorporate nonattainment designations that affect the implicit marginal cost of emissions in the polluting sector. We take nonattainment designations to be exogenous so that the potential reallocation of emissions across space does not endogenously induce a county to be in nonattainment.[7]

3.1 Household Problem

There is a mass L_j^m of households in each location j and sector m. We call (j, m) location-sector pairs *markets*. Households maximize a Cobb-Douglas utility function by choosing a market (i, k) to work and live, potentially choosing to be nonemployed ($k = 0$):

$$U_j^m = \max_{i \in 1,\ldots,N, k \in 0,\ldots,K} \; B_i^k \delta_{ji}^{mk} \prod_{l=1}^{K} \left(C_i^l\right)^{\alpha^l}.$$

Households consume a set of local final goods C_i^l where C_i^l is a constant elasticity of substitution (CES) aggregate of sector l varieties with an elasticity of substitution of σ^l. The parameter α^l is the consumption share of sector l where $\sum_{l=1}^{K} \alpha^l = 1$. $\delta_{ji}^{mk} \in (0, 1]$ is the cost

[6] We abstract away from offshoring dirty production outside the United States. Previous work indicates that declining emissions rates in US manufacturing rather than offshoring is responsible for the overall decline in US manufacturing emissions (Kahn, 2003; Levinson, 2009, 2015; Shapiro and Walker, 2018).

[7] 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.

of moving from market-sector pair (j, m) to market-sector (i, k) in consumption terms and B_i^k captures amenities in location i. 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 sector k for final consumption in county i, defined below. A consumer's indirect consumption utility V_i^k is their real wage if employed, and is equal to home production b_i if nonemployed:

$$V_i^k = \prod_{l=1}^{K} \left(C_i^l\right)^{\alpha^l} = \begin{cases} \frac{w_i^k}{P_i} & \text{if } k = 1, \ldots, K \\ b_i & \text{if } k = 0 \end{cases} \tag{1}$$

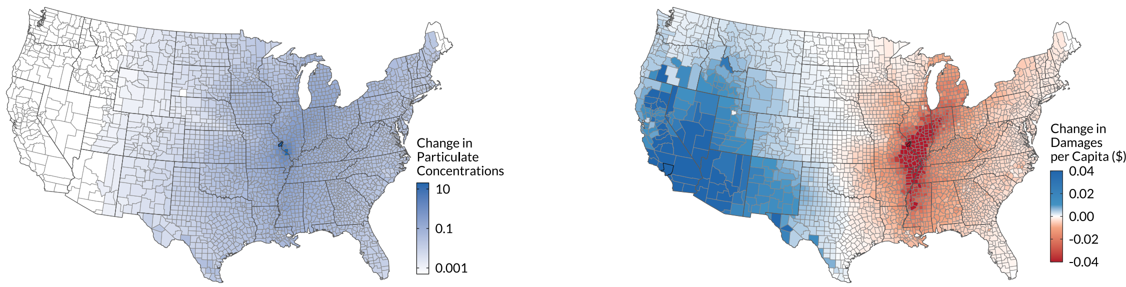
Location-specific amenities B_i^k are determined by a host of local factors including ambient pollution concentrations. Local ambient pollution a_i is a function of emissions in all locations: $a_i = A_i(\boldsymbol{e})$ where $\boldsymbol{e} = (e_1^1, \ldots, e_N^1, \ldots, e_1^2, e_N^2, \ldots, e_1^P, \ldots, e_N^P)$ 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 a_i. For example, ammonia, nitrogen oxides, sulfur dioxide, and volatile organic compounds are precursors to ambient particulate matter. Second, emissions can move across counties, and therefore affect ambient concentrations and amenities in other locations, imposing cross-county externalities.

We specify A_i as the atmospheric transportation model in the Air Pollution Emission Experiments and Policy Version 3 (AP3) model (Muller and Mendelsohn, 2009; Muller, Mendelsohn and Nordhaus, 2011; Tschofen, Azevedo and Muller, 2019; Clay, Jha, Muller and Walsh, 2019), a widely used integrated assessment model for measuring the economic damages from emissions of air pollutants. The atmospheric transportation model in AP3 simulates how one ton of pollutant p emitted in any county i translates into changes in ambient concentrations of fine particulate matter ($PM_{2.5}$) in all counties in the United States.[9] The left panel of Figure 1 provides an example to illustrate the geographic structure of A_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 when emitted in St. Louis. The figure shows that the effect of emissions on concentrations declines roughly exponentially in space,

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

[9] In AP3 $PM_{2.5}$ concentrations in a county i are given as a linear combination of emissions from all counties.

Figure 1: Comparison of $PM_{2.5}$ concentrations and air quality damages of emissions from St. Louis and Los Angeles.



Note: The left map shows changes in $PM_{2.5}$ concentrations caused by one thousand metric tons of nitrogen oxides emissions in St. Louis County, MO. The units for the change in $PM_{2.5}$ is micrograms per cubic meter. The right map shows changes in damages per capita from moving 1000 metric tons of nitrogen oxide emissions from St. Louis County, MO to Los Angeles County, CA.

significantly increasing concentrations near St. Louis but essentially having no effect on the West Coast.

Moving from emissions to amenities requires translating changes in concentrations into consumption-equivalent terms. We do this by drawing on the concentration-damage model in AP3 that maps changes in local ambient pollution a_i into monetized per capita damages d_i as a function $d_i = D(a_i)$. This function combines a concentration-mortality risk relationship from the epidemiology literature with an estimate of the value of a statistical life to put impacts in dollar terms.[10] We focus on damages caused by mortality from particulate matter exposure because it accounts for over 90 percent of the estimated damage from pollution sources that are regulated by the NAAQS. Other pollutants (e.g., ozone) and non-mortality forms of damage (e.g., hospitalizations, effects on agriculture, and recreation) account for the remainder (US Environmental Protection Agency, 1999, 2011, p. 7-15). The right panel of Figure 1 shows how per capita damages would change if the one thousand metric tons of nitrogen oxides were to be emitted in Los Angeles instead of St. Louis. Gains and losses are concentrated near the two counties of interest, however there are non-negligible welfare impacts across the entire United States.

The atmospheric transportation model and concentration-response functions allow us to express the marginal damage caused by one ton of pollution emitted in county j on one worker in county i in dollar terms as $md_{ij} := \frac{\partial d_i}{\partial e_j} = \frac{\partial D(a_i)}{\partial a_i}\frac{\partial A_i(\boldsymbol{e})}{\partial e_j}$. We translate monetized damages into consumption-equivalent terms by expressing damages as a fraction of real wages

[10] Muller and Mendelsohn (2007) provide a detailed description of an earlier version of the model.

or home production. Specifically, amenities are given by:

$$B_i^k = \bar{B}_i \left[1 - \frac{\sum_{j=1}^{N} \sum_{p=1}^{P} md_{ij}^{p} e_j^{p}}{V_i^k} \right] \tag{2}$$

where $\bar{B}_i$ is the baseline level of amenities and the second term captures the reduction in amenities. Since we do not observe home production $b_i = V_i^0$, we assign V_i^0 to be the population-weighted average real wage in location i for the purpose of computing changes in amenities within the quantitative model.

Labor is mobile across counties and sectors, 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 $k = 0, \ldots, K$.[11] 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 is drawn from a Fréchet distribution. This implies the share of households that move from (j, m) to (i, k) is:

$$\pi_{ji}^{mk} = \frac{V_i^k B_i^k \bar{\delta}_{ji}^{mk}}{\sum_{n=1}^{N} \sum_{l=1}^{K} V_n^l B_n^l \bar{\delta}_{jn}^{ml}}. \tag{3}$$

This reflects the fact that a household is more likely to move from (j, m) to (i, k) if (i, k) has higher 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 a version of equation (3) to estimate household migration responses to nonattainment as a way to validate that labor observes and responds to nonattainment-induced changes in ambient pollution. First, we show that, conditional on real wages, households are more likely to move into a county that goes into nonattainment relative to a county that does not. This suggests that households are responding to the pollution impacts of nonattainment. Second, we show that this estimate captures the *total* reduced-form effect of a county's nonattainment status on its own amenities. Conditional on real wages, variation in migration captures all of the possible pathways through which nonattainment status improves local amenities (e.g. reductions in noise, or improved foliage from better air quality). This provides an upper bound on the size of the local amenities' effect in our quantitative exercises. Consistent with this intuition we find the reduced form

[11] Moving costs can be thought of as capturing actual expenditures for moving locations or jobs as well as other costs like temporary unemployment (Walker, 2013).

estimate is about double the size of our quantitative results for amenity improvements.

3.2 Firm Problem

Perfectly competitive firms use a Cobb-Douglas technology to produce different varieties of goods by combining labor $L_i^k(\omega)$, capital $K_i^k(\omega)$, and emissions $e_i^{kp}(\omega)$ of pollutant p:

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

where ω denotes different varieties, $p = 1, \ldots, P$ indexes different pollutants, $\gamma \in [0,1]$ is the labor share, $1-\gamma$ is the capital share, and capital is perfectly mobile across space and sectors. The parameter ξ^{kp} is the elasticity for pollutant p. This model is isomorphic to one in which the firm operates a Cobb-Douglas production technology with labor and capital as inputs, emissions as a byproduct, and the use of an abatement technology for emissions (Copeland and Taylor, 2013). One unit of output generates one unit of emissions subject to the appropriate normalization of units.[12] To simplify the exposition, going forward we omit varieties from the notation whenever the mathematics remains clear.

For each market, $z_i^k(\omega)$ is the productivity or efficiency of variety ω. Following Eaton and Kortum (2002), we assume that $z_i^k(\omega)$ is a random variable distributed according to the Fréchet distribution:

$$F_i^k(z) = \exp\left(-T_i^k \, z^{-\theta^k} \right) \tag{4}$$

where $\theta^k > 1$ is the trade elasticity parameter common across all counties and measures the level of intra-sector 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.

3.2.1 Emissions

In equilibrium, expenditures on emissions are a constant share of revenues, $\eta_i^{kp} e_i^{kp} = \xi^{kp} P_i^k q_i^k$, which we can rearrange to get an expression for equilibrium emissions intensity per unit of

[12] $e_i^{kp}/q_i^k = 1$ implies that we can substitute q_i^k into the right-hand side of the production function and recover a standard capital-labor input production function. Emissions abatement thus reduces emissions below q_i^k and acts to reduce output.

output:

$$\frac{e_i^{kp}}{q_i^k} = \frac{\xi^{kp} P_i^k}{\eta_i^{kp}} \tag{5}$$

where P_i^k is the sector 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. η_i^{kp} represents the impact of all existing environmental regulations on the firms' operating costs. 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 will estimate β_η^p, which is the effect of entering nonattainment on the emissions price in percentage terms.

3.2.2 Prices and Market Clearing

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

$$c_i^k = \Omega \left[\prod_{p=1}^{P} \left(\eta_i^{kp}\right)^{\xi^{kp}}\right] \left[(r_i^k)^{1-\gamma} (w_i^k)^{\gamma}\right]^{1-\sum_{p=1}^{P} \xi^{kp}}, \tag{6}$$

where Ω is a constant, r_i^k is the capital rental rate and 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 one unit to be delivered and we assume that $\tau_{jj}^k = 1$ for all j, k. The price of some variety ω is the minimum cost across all counties:

$$p_i^k(\omega) = \min_{i=1,\ldots,N} \left\{\frac{c_j^k \tau_{ij}^k}{z_i^k(\omega)}\right\}.$$

The Fréchet distribution assumption for productivity gives us that the price index is:

$$P_i^k = \kappa \left(\sum_{n=1}^{N} T_n^k \left[c_n^k \tau_{in}^k\right]^{-\theta^k}\right)^{-1/\theta^k} \tag{7}$$

where κ is a constant. A transformation of the price index, $(P_i^k)^{-\theta^k}$, 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:

$$FMA_i^k = \sum_{j=1}^{N} \frac{\tau_{ji}^{-\theta^k} Y_j^k}{CMA_j^k} \tag{8}$$

which captures firms' access to larger markets, where Y_j^k is output in market (k, j). These terms are equivalent up to a normalization and so we define market access MA_i^k as:[13]

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

where ρ is a constant.

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

$$X_{ij}^k = \kappa T_j^k Y_i^k \left(\frac{c_j^k \tau_{ij}^k}{P_i^k} \right)^{-\theta^k}. \tag{9}$$

We define trade shares as the share of i's sector k expenditures on j:

$$\lambda_{ij}^k = \frac{X_{ij}^k}{\sum_{h=1}^{N} X_{ih}^k} \tag{10}$$

and i's total sector k expenditures as:

$$X_i^k = \sum_{h=1}^{N} X_{ih}^k. \tag{11}$$

Finally, market clearing requires:

$$w_i^k L_i^k = \gamma \left(1 - \sum_{p=1}^{P} \xi^{kp} \right) \sum_{h=1}^{N} X_h^k \lambda_{hi}^k. \tag{12}$$

Equilibrium Definition: Given model primitives T_i^k, B_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, rental rates r, prices P_i^k, emissions e_i^{kp}, and labor L_i^k for $i = 1, \ldots, N$, $k = 1, \ldots, K$, and $p = 1, \ldots, P$ such that equations (3) through (12) are satisfied.

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

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 NAAQS 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. The data include whether a county is in full or partial nonattainment under the standards set for 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.

4.2 Emissions

Data on emissions come from the National Emissions Inventory (NEI). The NEI reports emissions of a wide range of pollutants at point sources. 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 particulate matter. Our main estimates for effects on emissions use data from 1990 and the 1996–2001 period. The gap reflects the years in which the NEI was conducted. Section D of the appendix we use shorter panels to test for robustness.

4.3 Economic Activity by Sector

We draw on data from the Bureau of Economic Analysis to capture county-level economic activity by sector. Specifically, we use information on payroll and employment by sector. We aggregate the sector-level data to groups that encompass polluting and nonpolluting sectors. For the polluting sector, we focus on manufacturing and exclude utilities. For the nonpolluting sector, we include sectors outside of both manufacturing and utilities, which are primarily services. Fossil fuel plants emit a wide range of criteria pollutant precursors, but are a primary focus of the the Acid Rain Program – another new regulation under the 1990 CAA amendments that is not the focus of our analysis.

4.4 Migration and Mobility Across Industries

We compute cross-county migration shares using tax return data from the Internal Revenue Service's (IRS) SOI Tax Stats data. The IRS has reported 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 is that the IRS data do 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 sector of employment, including nonemployment, among other variables. The Current Population Survey follows individuals for four months, and then for another four months with an eight-month gap in between the two spells. We use the sector 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 nonpolluting sectors, and nonemployment. 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 sectors 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, which we construct following the approach in Combes and Lafourcade (2005). To start, we find the routes with the shortest travel times between all county pairs in 1980, 1990, and 2000. To do this we combine newly digitized shapefiles of the US highway network in 1980 and 1990 (Jaworski and Kitchens, 2021) with readily available shapefiles for the US highway network in 2000 (US Department of Transportation, 2021); we then use Djikstra's algorithm to find the quickest 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 costs 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.[14] This requires calibrating the trade elasticity θ^k, which we set to four as in (Simonovska and Waugh, 2014).

5 Estimating the Effect of Nonattainment on Emissions

The model in Section 3 allows us to estimate the impact of nonattainment on the local implicit marginal cost of emissions in an internally consistent way. We use equation (5) together with the expression for labor's share of firm revenues to obtain an expression for emissions intensity – relative to labor costs, not output – as a function of nonattainment status, emissions elasticities, and the unobserved base emissions price:

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

We estimate difference-in-differences specifications that exploit county-level variation in nonattainment status 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 intensity comes from comparing emissions in attainment and nonattainment counties, before and after a new nonattainment designation under the 1990 amendments.

[14] This is a version of the system expressed in equation (8). The solution to this system is unique up to a constant.

Our estimating equation is:

$$\log\left(\frac{e^p_{i,t}}{w_{i,t}L_{i,t}}\right) = -\beta^p_\eta N_{i,t} + \psi_i + \nu^p_t + \varepsilon^p_{i,t} \tag{13}$$

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 marginal damage and response to nonattainment of each pollutant, but we also estimate a combined effect as a robustness check.

We use county (ψ_i) and pollutant-year ($\nu_{p,t}$) fixed effects to control for the unobserved base implicit emissions price induced by other overlapping environmental regulations. Standard errors are clustered at the county level to account for autocorrelation of the error term.

There are two main potential threats to identification. The first is underlying economic growth causing additional emissions and driving a county into nonattainment. The second is a Stable Unit Treatment Value Assumption (SUTVA) violation where nonattainment induces emissions leakage to attainment counties. The potential economic growth identification problem would bias our estimates toward suggesting that nonattainment actually increases emissions, while the potential SUTVA problem would bias us toward finding too large of a reduction in emissions if there is positive leakage of emissions.

The economic growth identification threat is addressed by estimating the effect on emissions intensity which accounts for the scale of the local economy. The SUTVA threat can be assessed by the quantitative model which allows us to measure the extent of leakage. Our model results suggests that there is actually a small amount of negative leakage – reductions in emissions in attainment counties – so that our estimates would be slightly biased toward zero.

Table 1 reports our estimates based on equation (13). Panel A reports the average effect on our five emitted pollutants of any nonattainment designation. Columns 1 and 3 include county, pollutant, and year fixed effects. Columns 2 and 4 replace the pollutant fixed effects and year fixed effects with pollutant-year fixed effects. Columns 1 and 2 use the level of emissions as the outcome. Columns 3 and 4 instead use emissions intensity, consistent with the model. 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. The results across all four columns are highly consistent and indicate that nonattainment raises the implicit marginal cost of emissions by 60 percent. Directly interpreting the estimate from the estimating equation, nonattainment drives a 40 percent reduction in emissions intensity.

Panel B repeats the same exercise as Panel A, but reports estimates for the pollutant-specific effects of a nonattainment designation. The pollutant-specific effects in Panel B

Table 1: Estimated effect of nonattainment on the implicit marginal cost of emissions.

	(1)	(2)	(3)	(4)
	Emissions ($\log e_i^{kp}$)		Emissions Intensity $\left(\log \frac{e_i^{kp}}{w_i^k L_i^k}\right)$	
A. Combined				
β_η^p	0.35**	0.35**	0.48*	0.48*
	(0.15)	(0.15)	(0.26)	(0.26)
B. By Emitted Pollutant				
Ammonia ($\beta_\eta^{NH_3}$)	2.0***	1.9***	2.4***	2.3***
	(0.39)	(0.39)	(0.74)	(0.74)
Nitrogen Oxides ($\beta_\eta^{NO_x}$)	0.47**	0.50***	0.36**	0.38**
	(0.19)	(0.19)	(0.15)	(0.15)
Fine Particulates ($\beta_\eta^{PM_{2.5}}$)	0.17	0.18	0.67	0.68
	(0.26)	(0.27)	(0.43)	(0.42)
Sulfur Dioxide ($\beta_\eta^{SO_2}$)	0.24	0.23	0.43	0.43
	(0.21)	(0.21)	(0.32)	(0.32)
Volatile Organics (β_η^{VOC})	0.42**	0.40*	0.57	0.56
	(0.20)	(0.20)	(0.40)	(0.41)
Observations	70225	70225	70225	70225
County FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	No
Pollutant FEs	Yes	No	Yes	No
Pollutant-Year FEs	No	Yes	No	Yes

Note: The table shows estimates for versions of equation (13). Each coefficient can be interpreted as a semi-elasticity, the percent change in emissions. Panel A reports estimates of the coefficient on nonattainment status. Panel B reports estimates of the coefficient on nonattainment status interacted with a dummy variable for each pollutant. Columns 1 and 3 only include county, year, and pollutant fixed effects; Columns 2 and 4 replace the year and pollutant fixed effects with pollutant-year fixed effects. Columns 3 and 4 include the wage bill control and fix the coefficient at its theoretically-consistent value of one. Robust standard errors clustered at the county level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

highlight the extensive heterogeneity in the effects of nonattainment on emissions of different pollutants: the price of emissions on ammonia goes up by nearly an order of magnitude, the price of fine particulates doubles, the price of volatile organic compounds goes up by 75 percent, and the prices of nitrogen oxides and sulfur dioxide go up by 50 percent.[15] Again, directly interpreting equation (13), emissions intensities under nonattainment drop by between 30 percent to 90 percent depending on the pollutant.

6 Results

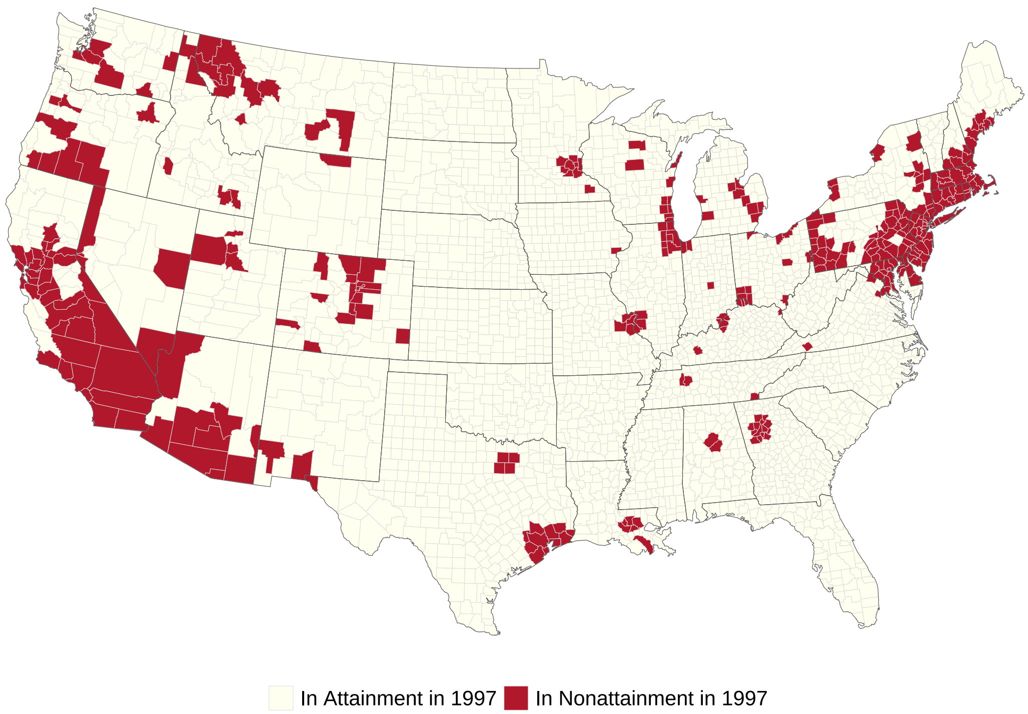
In this section, we simulate counterfactual scenarios using the quantitative model and our estimated effects of nonattainment from Column 4 of Panel B of Table 1. We use 1997 as our benchmark year and choose the model parameters using estimates from the previous section or values taken from the literature. We summarize these values in Table C1 in the appendix. In our first set of results we quantify the welfare impacts of the 1997 nonattainment designations and three counterfactual policies: (1) implementing the 2022 pollution thresholds for assigning nonattainment designations, but in 1997, (2) requiring all counties to take up nonattainment county practices (i.e. putting all counties into nonattainment), and (3) using the first-best emission price policy. In our second set of results we show the geographic effects of the 1997 nonattainment designations and highlight the importance of general equilibrium responses. All results are relative to a counterfactual of no nonattainment designations. Figure 2 shows the set of counties that are shocked with nonattainment designations in 1997. Section B shows how we simulate the counterfactuals and compute welfare. We report welfare in terms of consumption-equivalent compensating variation. When reported as percents, our reported welfare numbers are the the percent change in real wages that would generate the same welfare impact as the nonattainment shock. We also report welfare in dollars by translating the percentage effects using local real wages. Welfare in dollar terms therefore does not account for impacts on nonemployed workers who do not receive market wages.

6.1 Aggregate Impact

Figure 3 plots the aggregate welfare impacts of a set of various NAAQS pollution thresholds for assigning counties as in nonattainment relative to the welfare impact if no counties were in nonattainment (or a situation where nonattainment were to have no binding effect). The

[15] The large relative effect on ammonia is consistent with evidence that marginal abatement costs for ammonia are low compared to other particulate precursors (Gu et al., 2021).

Figure 2: Counties in nonattainment in 1997.



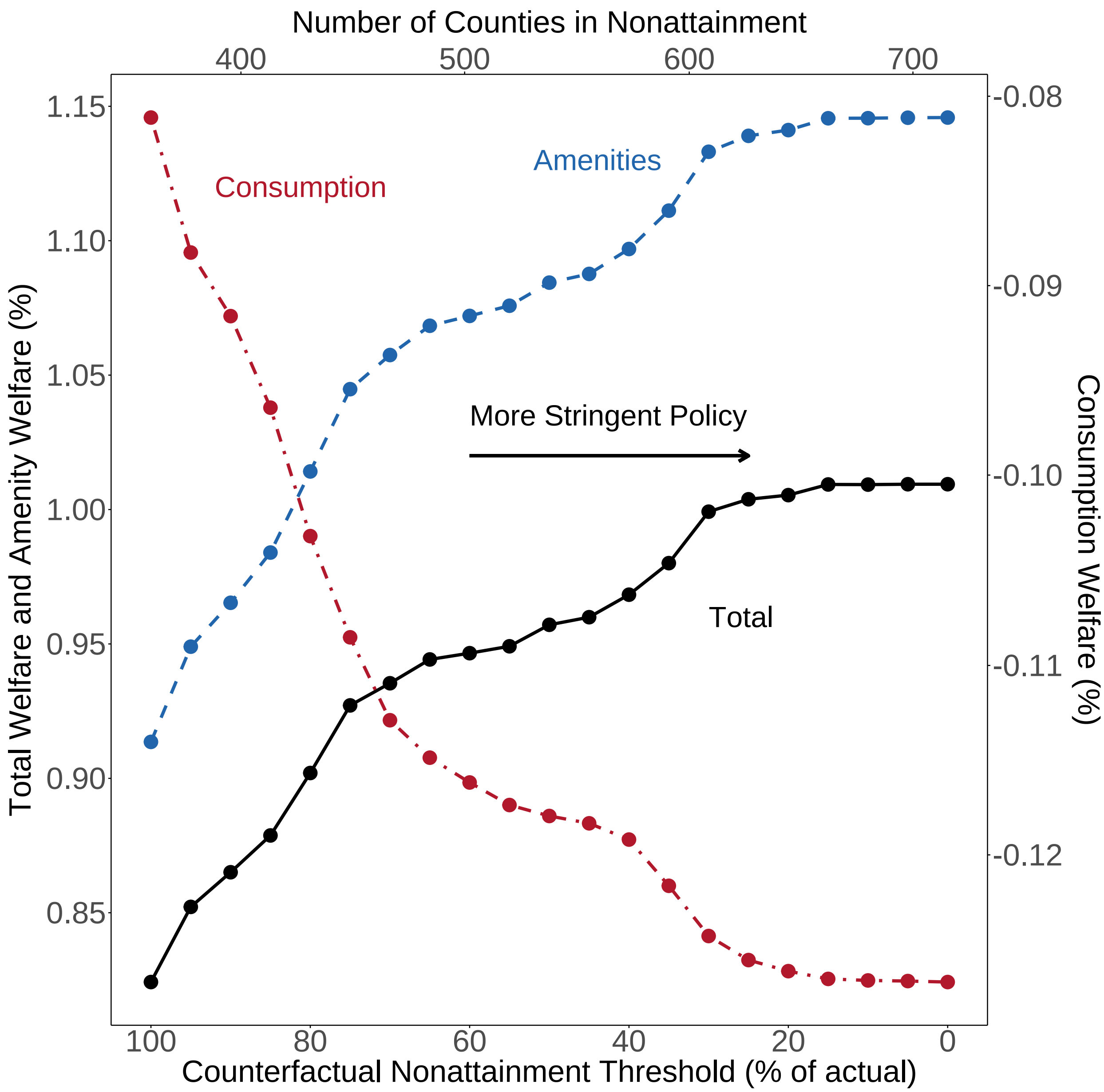
Notes: The map indicates in red all counties in nonattainment in 1997.

purpose of this exercise is to show the aggregate welfare impact of the 1997 nonattainment designations and then trace out the welfare impact of making them more stringent. The points farthest to the left on the figure correspond to the actual set of nonattainment designations in 1997, when approximately 400 counties were in nonattainment as indicated by the top x axis. These points report the welfare impact of the actual nonattainment designations in the data. Moving to the right increases the stringency of the concentration thresholds for nonattainment designations uniformly across pollutants where the counterfactual threshold as a fraction of the actual threshold in the real world is given by the bottom x axis. For example, in the middle of the figure, the NAAQS thresholds are set to 50% of the real-world thresholds (i.e., twice as stringent), while the points farthest to the right put every county with a pollution monitor in nonattainment. Note that this does not actually force pollution to be zero in the model, but just forces all counties to adopt the technologies and practices mandated by a nonattainment designation.[16]

The figure presents three new facts about the NAAQS. First, the actual set of nonattain-

[16]Most counties do not have NAAQS pollution monitors. Since we do not observe pollution concentrations in these counties, we cannot determine when they should be put into nonattainment in this counterfactual exercise.

Figure 3: Aggregate welfare impact of 1997 nonattainment designations and more stringent thresholds for assigning nonattainment.



Note: The left y-axis reports welfare results for total welfare and amenity welfare. The right y-axis reports welfare results for consumption. The bottom x-axis is the counterfactual pollution-concentration thresholds for nonattainment relative to the actual thresholds. The top x-axis indicates the number of counties in nonattainment. Moving to the right reduces the threshold (increases the stringency) of the counterfactual NAAQS. The solid black line reports total welfare. The dashed blue line reports amenity welfare. The dotted red line reports consumption welfare. Results presented in this figure only put counties with monitors in nonattainment; we do not observe pollution concentrations in counties without monitors.

ment designations generated welfare gains of 0.82 percent in consumption-equivalent terms, which is $57 billion annually for the employed sector. Amenity gains total 0.91 percent or $68 billion; consumption losses total -0.08 percent or -$11 billion. Consumption losses only accrue to employed workers. Second, the actual set of nonattainment standards in 1997 was not optimal. Reducing the nonattainment pollution concentration thresholds to under one-fifth their current levels, holding other aspects of the regulation fixed such as LAER or RACT definitions, could improve welfare by up to 0.18 percent or $13 billion in dollar terms. Third, despite the large gap in terms of stringency of the pollution threshold, the actual set of standards achieve 80 percent of the welfare gains of the best nonattainment pollution thresholds. The figure shows that making the NAAQS more stringent generates substantial amenities improvements, but also moderate consumption losses. Eventually, both impacts level off as the marginal nonattainment county becomes increasingly rural and less populated so that impacts on the aggregate economy decline in magnitude.

Panel A of Table 2 report additional results for the welfare impacts of the actual 1997 nonattainment designations, broke up by sector and county type. The first two columns report total welfare, the second two columns report amenity welfare, and the last two columns report consumption welfare. The first row of the table reports the aggregate welfare impacts of 0.82% or $57 billion which matches the left-most points in Figure 3. In Table D2 in the appendix we show that when omitting the relevant geography captured by our model – cross-county pollution transport, labor reallocation, and trade reallocation – benefits would only be 0.28% or $19 billion in the aggregate, with large losses predicted for manufacturing workers instead of moderate gains. This finding highlights the importance of economic geography for the evaluation of environmental policy.

We further decompose the aggregate welfare effect by sector and county nonattainment status. The second row of Panel A of Table 2 shows that workers in the manufacturing (polluting) sector are better off, but suffer substantial losses to real wages and consumption. The third row shows that workers in the nonmanufacturing (nonpolluting) sector obtain welfare gains of nearly 1 percent, or $55 billion. Nonmanufacturing workers have larger amenities gains and significantly smaller reductions in consumption welfare. The fourth row shows that nonemployed workers are better off because they do not suffer any consumption losses and reap the amenities improvements.

The next two rows in Table 2 show that the gains primarily accrue to nonattainment counties. Nonattainment counties see welfare gains of 1.1 percent (or $46 billion), but attainment counties have gains of 0.57 percent (or $11 billion). In aggregate terms, attainment counties reap a fifth of the total US welfare improvement, and a tenth of the amenities improvement, even though they were not directly affected by nonattainment. In total, about

Table 2: Welfare impacts of the 1997 and 2022 nonattainment standards, having all counties adopt nonattainment practices, and implementing first-best emissions pricing.

	Total		Amenity		Consumption	
	%	Billion $	%	Billion $	%	Billion $
A. 1997 Nonattainment						
Aggregate	0.82	57	0.91	68	−0.08	−11
Manufacturing	0.34	2	0.61	9	−0.42	−7
Nonmanufacturing	0.87	55	0.95	59	−0.05	−4
Nonemployed	0.96	–	0.96	–	–	–
Attainment Counties	0.57	11	0.5	7	0.08	4
Nonattainment Counties	1.1	46	1.33	61	−0.22	−15
B. 2022 Nonattainment						
Aggregate	0.96	63	1.08	77	−0.11	−14
Manufacturing	0.31	4	0.71	11	−0.61	−10
Nonmanufacturing	1.01	60	1.11	66	−0.06	−4
Nonemployed	1.17	–	1.2	–	–	–
Attainment Counties	0.73	12	0.75	13	−0.02	−1
Nonattainment Counties	1.24	51	1.43	63	−0.18	−12
C. All Counties in Nonattainment						
Aggregate	1.1	69	1.26	85	−0.14	−16
Manufacturing	0.28	4	0.82	12	−0.79	−12
Nonmanufacturing	1.16	66	1.28	73	−0.08	−4
Nonemployed	1.4	–	1.44	–	–	–
D. First-Best Emissions Pricing						
Aggregate	1.96	126	2.01	131	−0.04	−4
Manufacturing	1.42	17	1.31	18	−0.05	−1
Nonmanufacturing	1.96	109	2.05	112	−0.05	−3
Nonemployed	2.37	–	2.35	–	–	–

Note: Welfare is computed as the compensating variation of (A) the observed nonattainment status in 1997, (B) nonattainment status if 2022 NAAQS thresholds were implemented, (C) assigning all counties – including those without monitors – to be in nonattainment, or (D) first-best emissions pricing, relative to a counterfactual in which no counties are in nonattainment or face emissions pricing. The simulations account for labor reallocation, trade, and atmospheric transport of pollution. The first-best result sets the optimal location-specific nonnegative emission prices.

half of the total amenities benefits are from avoiding pollution that did not remain locally, but would have crossed over into other attainment and nonattainment counties. These two facts show that analyses omitting equilibrium effects and cross-county transport of emissions would miss a significant fraction of the welfare impacts of the NAAQS.

Panel B shows the welfare impacts of adopting the 2022 nonattainment thresholds instead of the 1997 thresholds. Relative to 1997, 2022 has increased stringency for nitrogen dioxide, ozone, and sulfur dioxide, and this would put about an additional 200 counties into nonattainment.[17] The nonattainment designations induced by the 2022 thresholds would further boost welfare by 0.14 percent (or $6 billion). This is borne primarily by nonmanufacturing and nonemployed workers because the amenities gains to manufacturing workers are offset by consumption losses. In the aggregate, amenities benefits would have been $9 billion higher and consumption losses only $3 billion lower if the NAAQS thresholds in 2022 would have been adopted sooner.

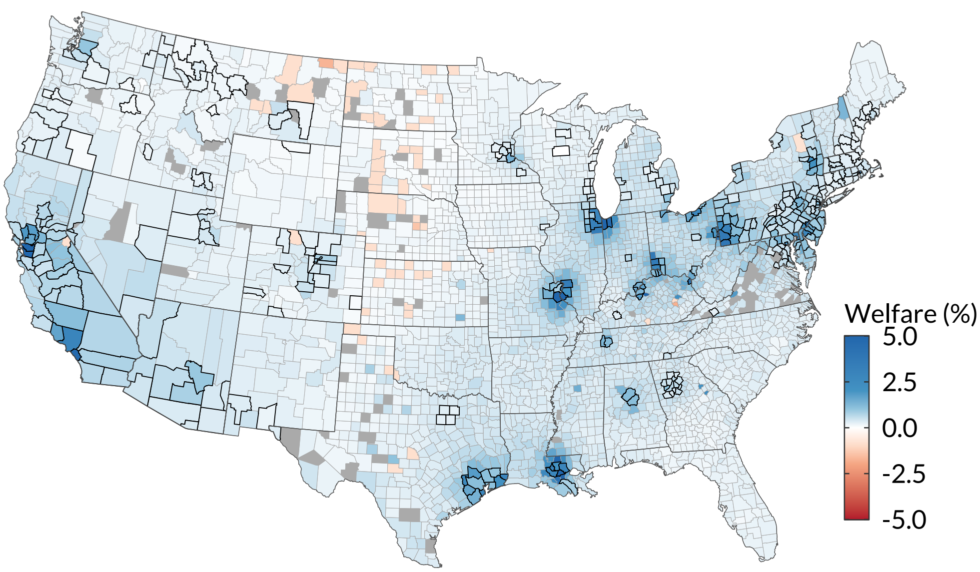
The remaining two panels show the impacts of policies that never occurred. Panel C shows the welfare impacts of putting every county in nonattainment, including those without monitors, so that all counties must adopt nonattainment abatement practices. This further improves welfare by another 0.14 percent with the benefits accruing to nonmanufacturing and nonemployed workers. This result suggests that broadening the abatement technology mandates under the NAAQS to all counties, not just nonattainment counties, may increase welfare.

Panel D shows the effects of using the first-best emission pricing scheme where emissions are priced equal to marginal damage. The first-best outcome improves welfare by more than twice the 1997 and 2022 nonattainment policies. The welfare difference is primarily driven by amenities improvements, but consumption losses are also generally smaller.

Table D2 in the appendix presents robustness checks of our quantitative results. We test the sensitivity of our results to different values of the trade elasticity, consumption share parameter, labor share, pollution elasticities, congestion and agglomeration, and allowing for marginal damages to increase in income. The most important parameter for the quantitiative results is the trade elasticity. Aggregate welfare is always positive for reasonable trade elasticity values, and manufacturing welfare is only negative for the highest trade elasticity value. The table also reports additional results showing that ignoring economic and physical geography leads to significantly different welfare predictions.

[17]For example, since 1997, a one-hour nitrogen dioxide standard was introduced, the ozone standard was revised to an 8-hour standard that was more stringent than the previous 1-hour standard, and a 1-hour sulfur dioxide standard was introduced.

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



Note: The change in welfare is the difference between the welfare calculated by the model using the 1997 nonattainment status provisions relative the welfare calculated under a counterfactual scenario in which no counties are in nonattainment. Welfare is calculated in terms of consumption-equivalent compensating variation; it can be measured as the equivalent welfare change from a percent change in consumption. Counties outlined in a dark border were in nonattainment in 1997. Dark gray counties are those that were omitted from the simulations due to missing data.

6.2 The Role of Economic Geography and Labor Reallocation

In this section we show the geography of the impacts of nonattainment designations. Figure 4 shows our main geographic result: the spatial distribution of the welfare impacts of 1997 nonattainment designations across all counties in our sample.[18] The areas in blue experience welfare gains while areas that experience losses are shown in red. The map provides an alternative depiction of the previous result in which nonattainment counties see large gains. The map reveals that there is substantial heterogeneity even within nonattainment counties with welfare impacts ranging from around zero in some Wisconsin nonattainment counties, to over 4 percent in areas elsewhere in the Midwest and California. In addition, the map makes clear that attainment counties nearby those in nonattainment in the Rust Belt and South also see substantial welfare improvements. Interestingly, the county that gained the most from the 1997 nonattainment designations – St. James, Louisiana – is actually in attainment.

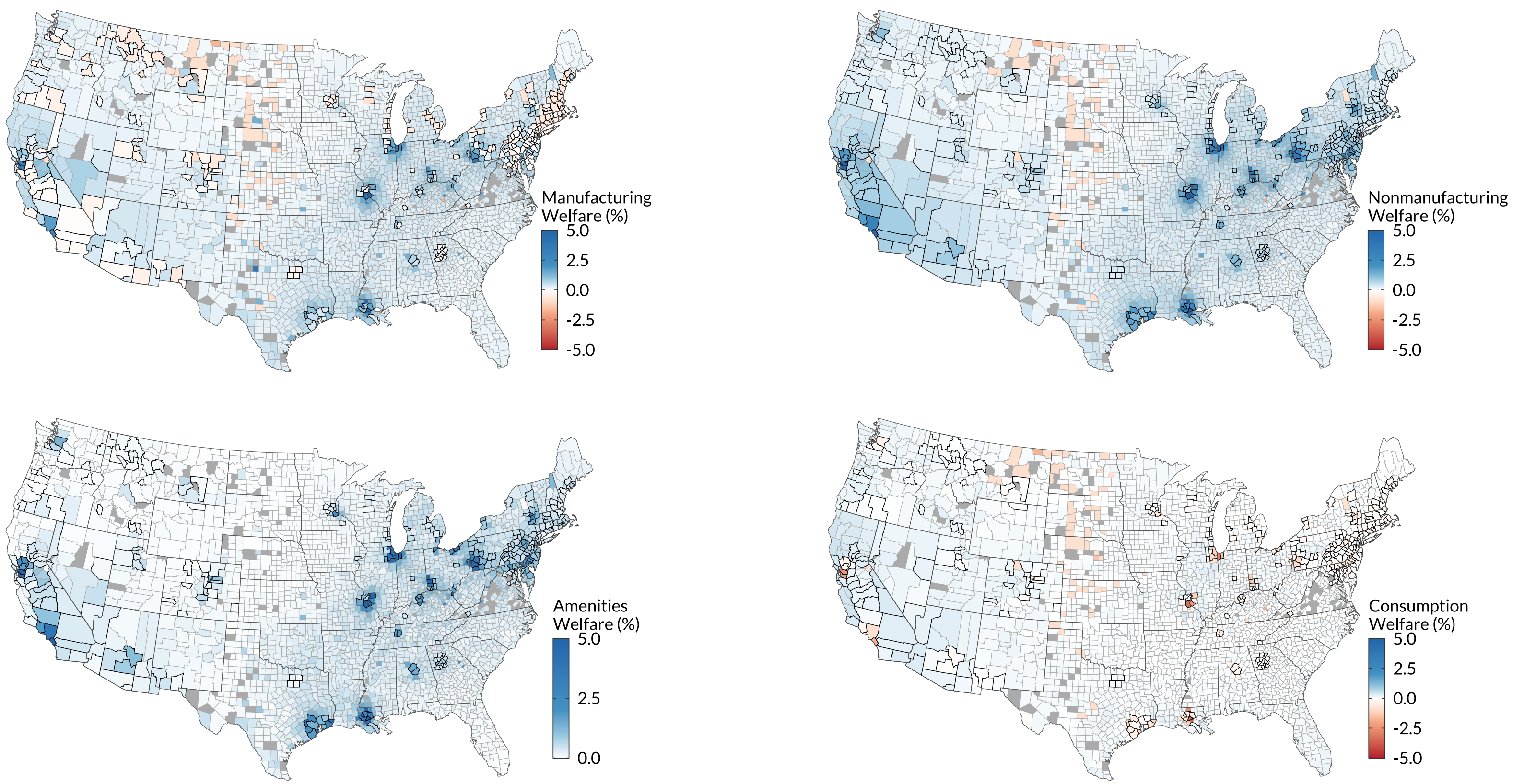
[18] An economic geography model is necessary to understand the spatial distribution of welfare because perfect mobility assumptions will ensure that welfare gains are uniform across space.

Figure 5 decomposes the welfare results along two margins. The top two maps show the welfare impact on manufacturing and nonmanufacturing workers. Manufacturing workers are marginally better off in most nonattainment counties despite large amenities improvements because nonattainment has large, negative effects on their real income. In nonattainment counties with large emissions reductions such as those around Chicago, New Orleans, or St. Louis, the amenities improvements dominate the real wage reductions resulting in welfare gains of over 1 percent. In attainment counties, manufacturing workers mostly experience welfare gains. Manufacturing workers in attainment counties have amenities improvements from avoided pollution transport, but also higher real wages from reduced competition in the labor market. The geography of nonmanufacturing welfare appears similar to the aggregate shown in Figure 4 because nonmanufacturing workers account for a majority of the population. Nonmanufacturing workers experience small consumption impacts and large amenities improvements.

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 that occur in nonattainment counties – leading to lower pollution concentrations everywhere. A major concern with spatially incomplete regulation of pollution is that more stringent regulation in one location will cause emissions to "leak" and increase in unregulated jurisdictions. We find the opposite. Emissions in attainment counties actually *decrease*, a phenomenon called "negative leakage" hypothesized by Baylis et al. (2014). 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 average real wages and consumption in attainment counties in Table 2), raising marginal costs of production, shrinking manufacturing output and emissions in attainment counties. Negative leakage generally accounts for 0.5 percent of the aggregate emissions decline depending on the pollutant. The right panel shows the change in welfare caused by changes in real wages and consumption. Consumption declines on average in nonattainment counties but increases in most attainment counties due to the increase in nominal wages that also caused negative leakage. In total, these two maps make clear that the welfare improvements for the largest beneficiaries under nonattainment status occur almost entirely through improved amenities.

Figure 6 shows the geography of labor mobility. The top left panel shows the aggregate change in population caused by nonattainment designations. Most attainment and nonattainment counties experience a decrease in population, indicating an increased concentration of workers in a few areas. Indeed, the map shows that nonattainment induced workers to

Figure 5: Change in manufacturing, nonmanufacturing, amenities, and consumption welfare from nonattainment in 1997.



Note: The change in welfare is the difference between the welfare calculated by the model using the 1997 nonattainment status provisions relative the welfare calculated under a counterfactual scenario in which no counties are in nonattainment. Welfare is calculated in terms of consumption-equivalent compensating variation; it can be measured as the equivalent welfare change from a percent change in consumption. Counties outlined in a dark border were in nonattainment in 1997. Dark gray counties are those that were omitted from the simulations due to missing data.

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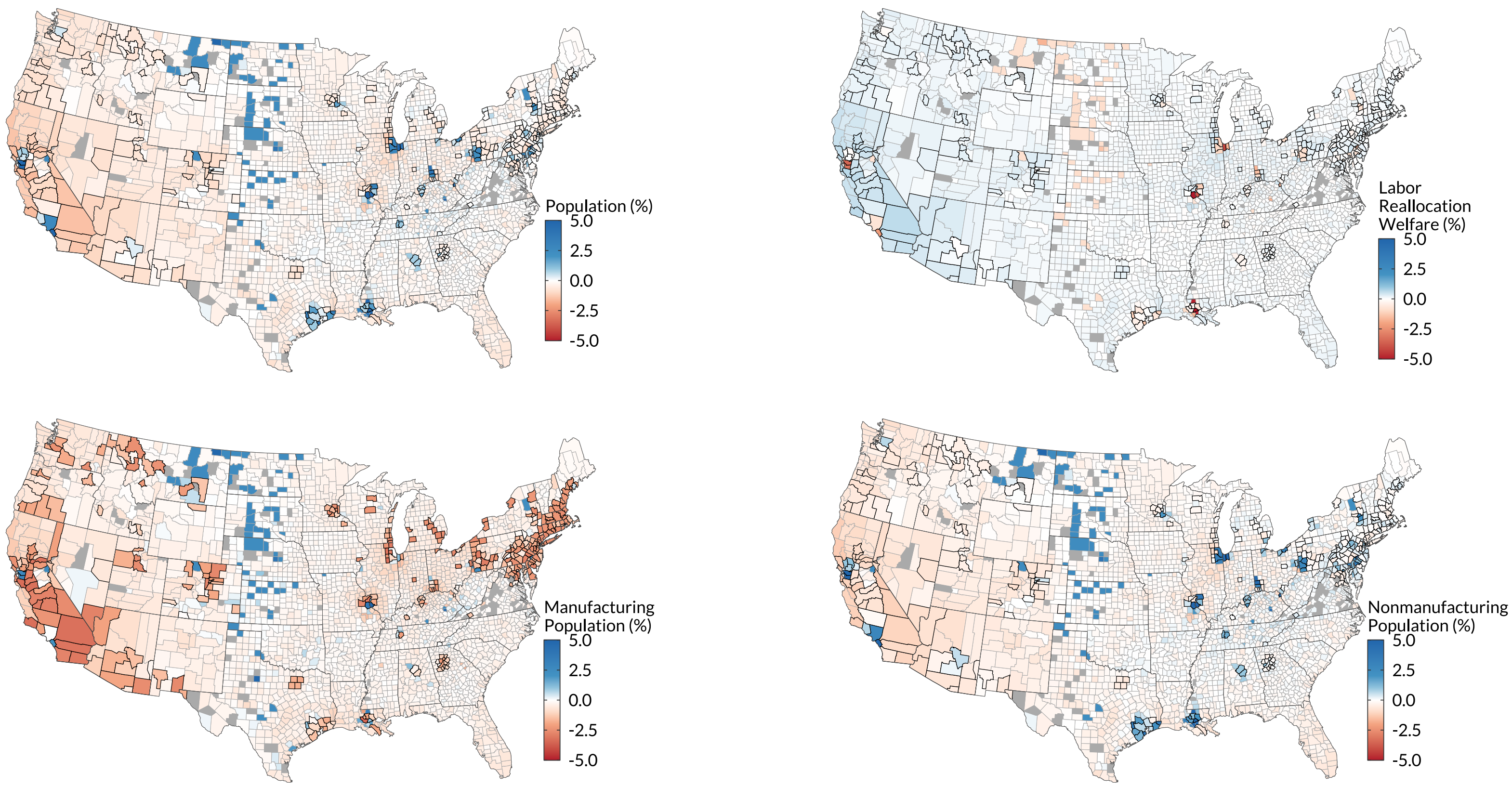
Figure 6: The change in population and welfare from endogenous labor reallocation.



Note: The top left panel shows the change in total population. The top right panel shows the change in total welfare from labor reallocation through migration and changing sector of employment. The bottom left panel shows the change in the manufacturing population. The bottom right panel shows the change in the nonmanufacturing population. The change in population is the percent change in county population calculated by the model using the 1997 nonattainment status provisions relative the population calculated under a counterfactual scenario in which no counties are in nonattainment. The change in welfare is the difference between the welfare calculated by the model using the 1997 nonattainment status provisions relative the welfare calculated under a counterfactual scenario in which no counties are in nonattainment. Welfare is calculated in terms of consumption-equivalent compensating variation; it can be measured as the equivalent welfare change from a percent change in consumption. Counties outlined in a dark border were in nonattainment in 1997. Dark gray counties are those that were omitted from the simulations due to missing data.

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move to the small set of cities that experienced the largest amenities improvements. Counties in the plains also experience a large *relative* influx of workers, but from a small baseline as these areas have small populations.

The top right panel shows the welfare value of workers in these counties being able to reallocate. In the aggregate, labor reallocation has a small positive aggregate effect on real wages and amenities of about 0.02%, but the map shows that this aggregate value masks significant heterogeneity. Less populous nonattainment counties outside major urban areas, such as California's Central Valley, tend to benefit from labor reallocation. Local amenities in these areas only moderately improve from emissions reductions, and incumbent workers are able to move to places with better real wages. These counties are better off by up to half a percent. Conversely, highly-populated nonattainment areas, such as St. Louis or Houston, tend to have significant amenities improvements since their baseline emissions levels are higher. The large amenities improvement in these areas makes incumbent workers better off, but it also makes the location more attractive to outside workers and induces them to migrate in. This intensifies labor market competition and depresses incumbent real wages, making incumbents worse off. Taken together, these results show that ignoring labor reallocation substantially overstates welfare improvements in major urban areas where labor market competition intensifies, and understates welfare improvements elsewhere because these workers can move into counties with improved air quality.

The bottom two panels break down the population changes into manufacturing and nonmanufacturing workers. Some nonattainment counties have population increases because of an influx of nonmanufacturing workers attracted by the improved amenities shown in Figure 5. Workers leaving nonattainment counties – who are primarily manufacturing workers – migrate to counties in the Plains and to about 20 nonattainment counties with large amenities improvements.[19]

In addition to reallocation of workers across space shown in Figure 6, there is also reallocation of workers across sectors. In the aggregate, we find that 1997 nonattainment designations reduced manufacturing employment by 1 percent. Manufacturing workers changed jobs and entered the nonmanufacturing sector to get higher real wages, above and beyond the costs of switching their sector of employment.

Section E of the appendix provides additional geographic results. It shows the spatial distribution of welfare gains from trade reallocation, the impacts of accounting for potential congestion and agglomeration externalities, the impacts of accounting for potential productivity effects of nonattainment beyond raising emissions costs, and the benefits of the first-

[19]Note that some of the Plains counties experience significant gains in population, which reflects their small size.

best location-specific pricing policy versus the actual set of nonattainment designations. To summarize: (1) the value of reallocation through trade is generally small everywhere, (2) accounting for congestion and agglomeration further decreases welfare gains in major cities compared to an analysis ignoring general equilibrium effects, (3) negative productivity effects consistent with the reduced form literature or positive productivity effects reflecting the strong version of the Porter hypothesis have little effect on aggregate welfare, and (4) using emissions pricing improves welfare in almost every county relative to the 1997 nonattainment designations.

7 Conclusion

In this paper we introduce an integrated spatial general equilibrium model to quantify the impacts of the National Ambient Air Quality Standards. The framework features economic geography forces that govern the spatial distribution of economic activity, the direct effects of regulation on emissions, and endogenous changes in amenities driven by endogenous emissions choices by firms. We use the framework to examine the welfare implications and distributional consequences of NAAQS under the Clean Air Act.

We find that the NAAQS delivers net benefits of over $50 billion annually, which substantially reflects the positive effect on amenities relative to the negative effects on real wages. In present value terms, this amounts to total benefits of nearly $2 trillion. We use the model to consider counterfactual policies and find that changes to nonattainment thresholds in the 2000s improved welfare by billions of dollars per year, but further welfare gains are possible through the widespread adoption of nonattainment practices or the use of emissions pricing.

In addition, we use the model to study the mechanisms underlying the spatial distribution of these effects. Specifically, workers are imperfectly mobile across sectors and locations, the spread of emissions is non-uniform across space and affected by 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 and labor reallocation are particularly important in our setting. Other factors that may matter for the ultimate welfare impacts of environmental regulation include market structure, heterogeneous preferences across households, and nonhomothetic preferences over housing or consumption. We leave these promising lines of research to future work.

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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 amenities similarly to how we represent the emissions price η_i^{kp} in the main text:

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

$\bar{B}_i$ 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 (3) 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 sector superscripts because we do not observe sector 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 sectors 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 percent in consumption-equivalent terms. Column 2 adds in the real wage control and fixes the coefficient on real wages to equal one to be consistent with the model. Column 3 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 between 3 and 4 percent.

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

	(1)	(2)	(3)
1(Dest. Nonattainment) - 1(Orig. Nonattainment)	0.040***	0.030**	
	(0.013)	(0.013)	
1(Destination Nonattainment)			0.030**
			(0.013)
1(Origin Nonattainment)			−0.029**
			(0.013)
Observations	704506	704506	704506
Origin-Destination FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Real Wage	Omitted	Coef. Fixed	Coef. Fixed
Origin vs Destination	Fixed	Fixed	Free

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

B Simulating Counterfactuals

B.1 Solution Algorithm

To simulate our counterfactual we need to invert the model and solve for the level of productivity T_i^k and the implicit marginal cost of emissions η_i^{kp}. We will not need to solve for the level of amenities B_i^k since observed migration shares are effectively sufficient statistics for the composition of moving costs and differences in base amenities across locations.[20]

First we solve for the baseline emission price. To recover η_i^{kp} we use the equilibrium condition for emissions intensity in equation (5) 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 marginal cost of emissions.

Next we solve for productivity. Combining equations (7) and (10) we have that:

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

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 MA_i^k as:[21]

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

We can manipulate equation (17) and obtain a system of equations that gives us T_i^k up to a normalization:

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

[20] If we observed county-level trade flows we could simulate counterfactuals without solving for T_i or estimating τ_{ji}.

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

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 must identify the market access variables MA_i^k to obtain productivity T_i^k for $k = 1, \ldots, K$. First, substitute MA_i^k into equation (18) for FMA_i^k and CMA_i^k, and recognizing 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 the factual 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 are given by: $\eta_i^{kp\prime} = \eta_i^{kp} \exp(\beta_\eta(N_i' - N_i))$.

We solve the model using four equilibrium conditions of the model. The first two are equations (19) and (20) along with the identity that $P_i^{k\prime} = (MA_i^{k\prime})^{-1/\theta^k}$ The remaining conditions pin down how migration and thus the labor distribution responds to the counterfactual change in amenities $N_j' - N_j$:[22]

$$\pi_{ij}^{km\prime} = \frac{\frac{V_j^{m\prime} B_j^{m\prime}}{V_j^m B_j^m} \pi_{ij}^{km}}{\sum_{l=1}^{K} \sum_{n=1}^{N} \frac{V_n^{l\prime} B_n^{l\prime}}{V_n^l B_n^l} \pi_{in}^{kl}} \tag{21}$$

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

where the V terms are real wages, $V_n^{0\prime} = V_n^0$ so that nonattainment does not change the payoff from nonemployment, and the counterfactual levels of amenities are computed by using equation (2) where the marginal damage term md_{ij}^p comes from the AP3 model and emissions and real wages are endogenous. With these equilibrium conditions, we can then solve for the set of endogenous variables given any counterfactual set of nonattainment designations across counties.

[22] 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.

B.2 Welfare Derivation

Recall that indirect utility from consumption and amenities is given by $V_i^k B_i^k$ and that migration shares are governed by $\pi_{ij}^{km} = \frac{V_j^m B_j^m \bar{\delta}_{ij}^{km}}{\sum_{l=0}^{K} \sum_{n=1}^{N} V_n^l B_n^l \bar{\delta}_{in}^{kl}}$. Rearrange and take the log of the expression for own-migration shares to get:

$$-\log \pi_{ii}^{kk} = \log \left[\sum_{l=0}^{K} \sum_{n=1}^{N} \frac{V_n^l B_n^l}{V_i^k B_i^k} \bar{\delta}_{in}^{kl} \right]. \tag{23}$$

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:

$$W_i^k = \log \left[\sum_{l=1}^{K} \sum_{n=1}^{N} V_n^l B_n^l \bar{\delta}_{in}^{kl} \right]$$

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

$$W_i^k = \log \left(V_i^k B_i^k \right) - \log \mu_{ii}^{kk}.$$

Define the compensating variation at some market (i, k) to be χ_i^k where:

$$W_i^{k\prime} = W_i^k + \log \chi_i^k$$

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 $\log \chi_i$:

$$\log \chi_i^k = \widehat{W}_i^k = \log \left(\widehat{V}_i^k \widehat{B}_i^k \right) - \log \widehat{\mu}_{ii}^{kk}.$$

C Quantitative Model Parameters

Table C1: Calibrated and estimated parameter values for quantitative model.

Parameter	**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^p_η)	
NH_3	2.3000
NO_x	0.3800
$PM_{2.5}$	0.6800
SO_2	0.4300
VOC	0.5600

Notes: The consumption share comes from Rudik et al. (2021) and is computed using the United States data from the 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 the marginal cost of emissions are our preferred estimates from Section 5.

D Robustness Checks

Sample Periods for Estimation Table D1 presents robustness checks of the effect of nonattainment on emissions prices with respect to the sample period. Our estimates are highly robust to the chosen years of inclusion.

Alternative Quantitative Parameters Table D2 reports the total welfare effects of the nonattainment counterfactual scenario but under different calibrated parameter values and structural assumptions.

Panel A shows the effect of changing 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 next three rows change the pollution elasticity parameters by halving, doubling, or quadrupling them. Greater pollution elasticities tend to dampen the overall welfare impact of the NAAQS. Manufacturing welfare decides in these runs because of lower real wages, but the other results remain the same.

Alternative Quantitative Structure Panel B shows the effect of making structural changes to the model. The first row of the panel introduces congestion and agglomeration externalities. With congestion externalities, amenities can be written as:

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

where B_i^k is amenities without congestion, and ζ^c is the congestion elasticity and equal to -0.3 following Allen and Arkolakis (2014). With agglomeration externalities, variety-specific productivity can be written as:

$$\tilde{z}_i^k(\omega) = z_i^k(\omega)\left[L_i^k(\omega)\right]^{\zeta^a}.$$

where $\zeta^a = 0.2$ following Allen and Arkolakis (2014). The existence of congestion and agglomeration slightly raises the aggregate benefits of nonattainment, although it increases the dispersion of welfare across sectors and counties.

The second row allows for marginal damages to depend on income, recognizing that richer people are willing to pay more to avoid mortality risk. Here we re-specify marginal damages as:

$$\widehat{md}_{ij}^k = md_{ij}\left(\frac{w_i^k}{\bar{w}_i^k}\right)^{\epsilon}$$

where $\epsilon = 0.4$ is the EPA's value of the income-elasticity of the value of a statistical life (VSL), and $\bar{w}_i^k$ is median household income. Marginal damages remain the same for the median household, but are increasing in income. Allowing for the VSL and marginal damages to be income-elastic decreases the benefits of the NAAQS by a quarter.

The third row presents results where we shut down all margins of economic and physical geography and shows why using a spatial model matters. In this model we do not allow labor to reallocate in response to the NAAQS, we do not allow trade patterns to change, and we shut down the ability of pollution to cross county borders. Ignoring geography leads to the largest relative change in the results of any parametric or structural change. The predicted welfare gains are less than one-third of the actual, manufacturing is predicted to lose by almost double of what it actually gains, and nonmanufacturing gains are understated by a half.

The final two rows show the effect of nonattainment additionally increasing or decreasing productivity (T_i^k) by 3 percent. 3 percent is about the productivity effect estimated in the prior literature (Greenstone et al., 2012) which does not distinguish between declines in productivity and increases in the cost of emissions. A decrease would be consistent with nonattainment making capital or labor less productivity because, for example, workers must now tend to abatement technology in addition to their regular tasks. An increase is consistent with the strong Porter hypothesis where environmental regulation leads to increased innovation and firm competitiveness. 3 percent changes in productivity has little effect in the aggregate, however it does increase manufacturing welfare by 75% or reduce it by 75% depending on the sign of the productivity shock.

Table D1: 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	0.51*	0.50*	0.34**	0.50*	0.49*	0.48*
	(0.28)	(0.27)	(0.15)	(0.26)	(0.26)	(0.26)
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

Table D2: Welfare impacts of nonattainment in 1997 under different model parameters or structural assumptions.

Change	Total %	Manuf. %	Nonmanuf. %	Attain. %	Nonattain. %
No Changes					
Base Model	0.82	0.34	0.87	0.57	1.1
A. Parameter Changes					
$\theta = 8$	0.46	-0.11	0.54	0.27	0.66
$\theta = 2$	1.8	1.24	1.71	1.59	2.14
$\alpha = 0.548$	0.82	0.34	0.87	0.57	1.1
$\alpha = 0.137$	0.82	0.34	0.87	0.57	1.1
$\gamma = 1$	0.81	0.43	0.86	0.49	1.12
$\gamma = 0.2405$	0.84	0.25	0.86	0.65	1.09
ξs Halved	0.85	0.53	0.87	0.57	1.14
ξs Doubled	0.78	-0.05	0.87	0.58	1.03
ξs Quadrupled	0.69	-0.83	0.86	0.61	0.87
B. Structural Changes					
Add Congestion/Agglomeration	0.9	0.21	1	0.52	1.26
VSL Increases in Income	0.59	0.2	0.64	0.37	0.81
No Economic/Physical Geography	0.28	-0.52	0.4	0.09	0.47
Decrease Productivity 3 Percent	0.85	0.6	0.87	0.57	1.16
Increase Productivity 3 Percent	0.79	0.09	0.86	0.58	1.05

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. Each row only makes one change relative to the base model in the first row.

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E Supporting Results

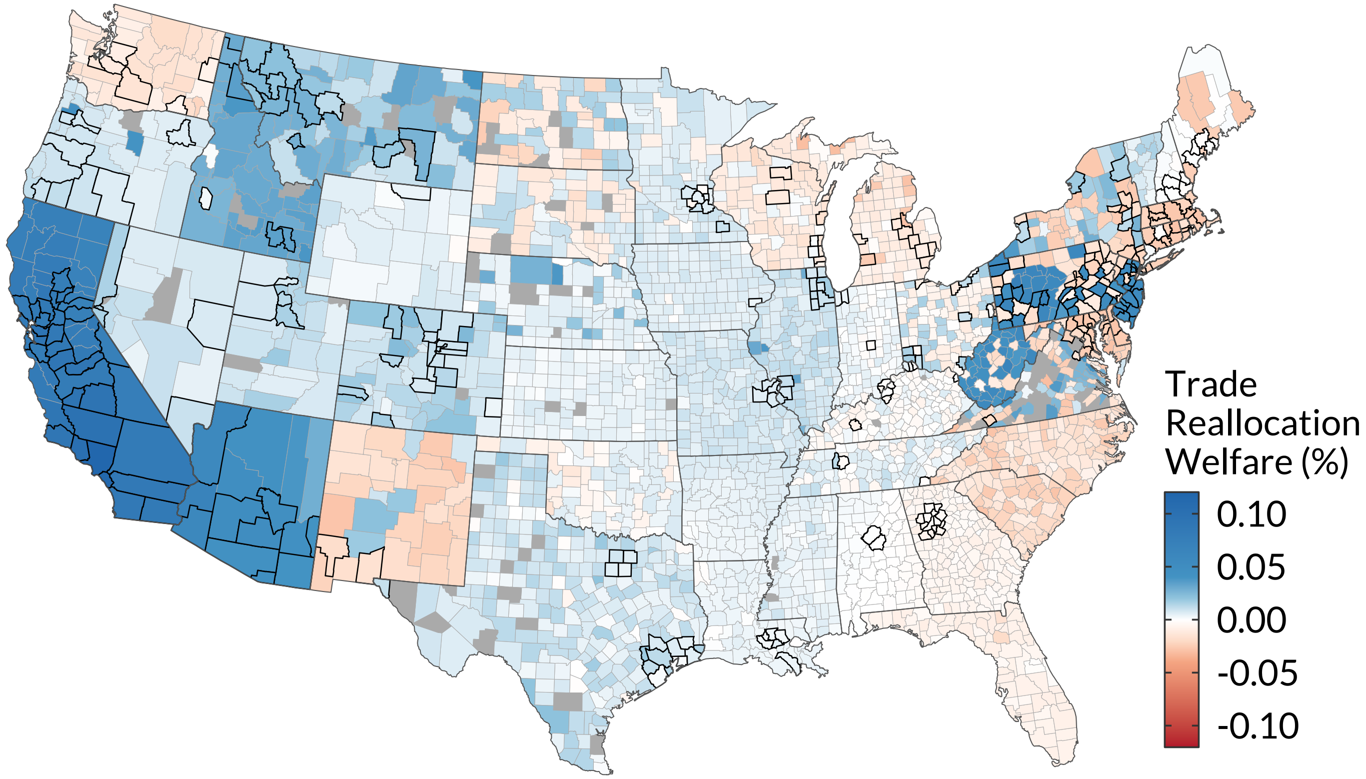
Welfare Value of Trade Reallocation Figure E1 shows that there is very little impact of reallocation through trade (i.e. changing market access), consistent with empirical work that finds it difficult to measure the impacts of environmental regulation through changing trade flows (Ederington, Levinson and Minier, 2005).

Congestion and Agglomeration Figure E2 plots the change in welfare through congestion and agglomeration. Similar to reallocation, congestion and agglomeration have highly heterogeneous welfare effects.

Productivity Effects Figure E3 plots the welfare impact of nonattainment if, in addition to its effect on emissions prices, it also has either a negative 3 percent or positive 3 percent effect on manufacturing productivity. Incorporating potential productivity effects does not meaningfully change the geography of the results.

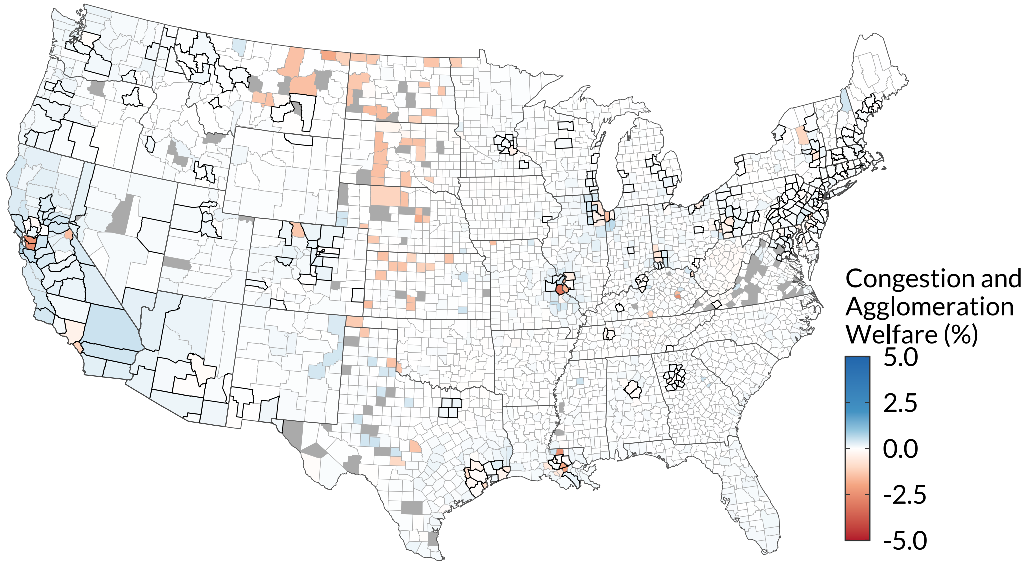
First-Best Versus Actual Figure E4 plots the welfare benefits of moving from the 1997 nonattainment designations to the first-best emission price policy. Counties in the east benefit most from emissions pricing. The lone county worse off with emissions pricing is Weston, Wyoming.

Figure E1: Value of reallocation through trade.



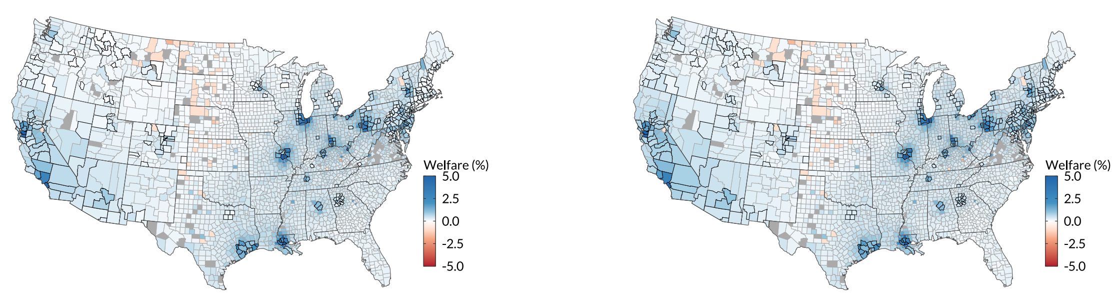
Note: The change in welfare is the difference between the welfare calculated by the model using the 1997 nonattainment status provisions relative the welfare calculated under a counterfactual scenario in which no counties are in nonattainment. Welfare is calculated in terms of consumption-equivalent compensating variation; it can be measured as the equivalent welfare change from a percent change in consumption. Counties outlined in a dark border were in nonattainment in 1997. Dark gray counties are those that were omitted from the simulations due to missing data. The figure shows the welfare impact of a model where market access changes endogenously to one where market access is fixed to its actual values.

Figure E2: Value of congestion and agglomeration.



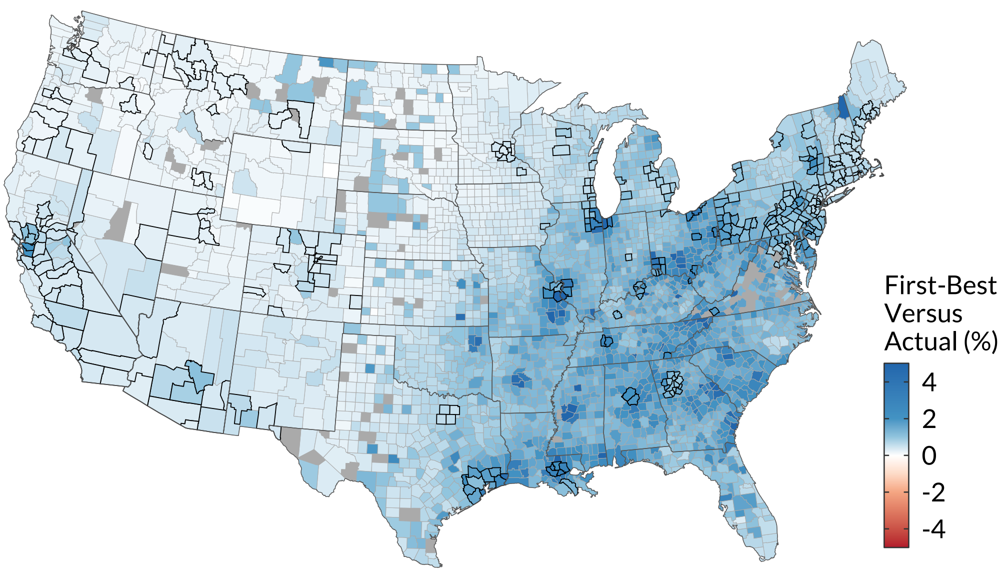
The change in welfare is the difference between the welfare calculated by the model using the 1997 nonattainment status provisions relative the welfare calculated under a counterfactual scenario in which no counties are in nonattainment. Welfare is calculated in terms of consumption-equivalent compensating variation; it can be measured as the equivalent welfare change from a percent change in consumption. Counties outlined in a dark border were in nonattainment in 1997. Dark gray counties are those that were omitted from the simulations due to missing data. The model includes congestion and agglomeration externalities.

Figure E3: Welfare from nonattainment in 1997 if there are additional -3% or $+3\%$ effects on total factor productivity in manufacturing.



Note: The left panel introduces an additional -3% productivity shock from nonattainment on top of the emissions price effects. The right panel introduces an additional +3% productivity shock from nonattainment on top of the emissions price effects. The change in welfare is the difference between the welfare calculated by the model using the 1997 nonattainment status provisions relative the welfare calculated under a counterfactual scenario in which no counties are in nonattainment. Welfare is calculated in terms of consumption-equivalent compensating variation; it can be measured as the equivalent welfare change from a percent change in consumption. Counties outlined in a dark border were in nonattainment in 1997. Dark gray counties are those that were omitted from the simulations due to missing data.

Figure E4: Change in county welfare from first-best relative to 1997 nonattainment.



Note: The change in welfare is the difference between the first-best relative to the model with the 1997 nonattainment status in effect. 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 in nonattainment in 1997. Grayed-out counties are omitted from the simulations due to missing data. The model includes impacts on emissions prices and allows for trade and labor mobility across counties and sectors.