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 impact of the leading air quality regulation in the United States: the National Ambient Air Quality Standards (NAAQS). We find that the NAAQS generate $40 billion in annual welfare gains, first-best emissions pricing would increase this by an additional $70 billion, gains are concentrated in a small set of cities, and improved amenities attract nonmanufacturing workers. Atmospheric transport of emissions, labor reallocation, and trade are first-order factors for quantifying the level and distribution of both costs and benefits of the NAAQS.

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1 Introduction

In the last several decades, governments around the world have enacted regulation intended to improve environmental quality. These protections benefit individuals through improved health, recreation, and other amenities. However, more stringent regulation of pollution 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, pollution transport across space, and heterogeneity across sectors and locations.

In this paper, we develop a novel quantitative framework to overcome these challenges that combines an Eaton and Kortum (2002)-style spatial equilibrium model with a benchmark integrated assessment model for air pollution (Mendelsohn and Muller, 2013).[1]Our model captures important features in economic geography and what we call physical geography. The economic geography in the model includes costly trade of goods and imperfectly mobile labor across locations and between sectors. Physical geography in our model allows for endogenous emissions and non-uniform atmospheric transport of local air pollution, which non-uniformly affects local mortality risk and thus local amenities. Accounting for endogenous responses and spatial transport of pollution is essential for understanding aggregate and distributional welfare impacts as both mechanisms distribute the costs and benefits of environmental regulation beyond places directly subject to regulation.

We use the model to study the equilibrium impact 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 standards for ambient concentrations of several 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, which captures the link between environmental regulation, the incentive to reduce emissions, and firm costs. This allows us to map regulation-induced changes in emissions to changes in local ambient pollution and local amenities across counties in the United States, while also accounting for endogenous responses to environmental regulation that drive further

[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 the model for environmental economic accounting and to measure mortality damages, while Clay, Jha, Muller and Walsh (2019) use the model 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.

changes in emissions, amenities, and prices.

To take the model to data, we estimate the effect of the NAAQS on emissions. To do this, we leverage quasi-experimental variation stemming from the 1990 CAA amendments, which increased regulatory scrutiny and costs to polluting firms by introducing a new class of pollutants under the NAAQS – particulate matter smaller than 10 micrometers in diameter (PM_{10}) – and scheduling a re-evaluation of the existing nonattainment designations.[2] Specifically, we estimate the impact of nonattainment on what we call the *regulatory shadow price of emissions*, which is the implicit marginal cost firms face for emitting each of five particulate matter precursors. We do so by comparing pollutant-specific emissions intensities before versus after the new nonattainment designations in attainment versus nonattainment counties. We find that the regulatory shadow price of emitting the five pollutants included in our model increases by an average of 60 percent with significant heterogeneity across pollutants.[3]

We then use our quantitative model to evaluate the impact of different sets of nonattainment designations as well as the first-best emissions pricing policy. In our main counterfactual experiment, we use the model to calculate the change in welfare, sectoral employment, and county population under the actual 1997 nonattainment designations relative to a counterfactual scenario in which no county was in nonattainment.[4] The results indicate that nonattainment designations led to a 0.66 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 0.57 percent or $40 billion per year. In present value terms at a 3 percent discount rate, total benefits are over $1 trillion.

To understand the forces driving the aggregate effects of the 1997 nonattainment designations we use the model to decompose the effects across sectors and space. Workers in both polluting and nonpolluting sectors are better off under the 1997 nonattainment designations, but to different degrees.[5] Workers in the polluting manufacturing sector suffer real wage losses

[2]Previous work provides reduced form evidence that nonattainment designations make 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]The five pollutants are ammonia (NH_3), nitrogen oxides (NO_x), fine particulate matter ($PM_{2.5}$), sulfur dioxide (SO_2), and volatile organic compounds (VOC). They are all precursors to $PM_{2.5}$, a subset of the newly regulated PM_{10}. One reason for heterogeneity in the effect on the regulatory shadow price of emissions would be heterogeneity in how a given quantity of the precursor pollutants translates into the ultimate regulated pollutant.

[4]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.

[5]The heterogeneity is fundamentally driven by mobility costs. In a frictionless world, indirect utility would be equalized across space and sectors.

of 0.40 percent, offsetting most of the welfare gains from improved amenities. Nonattainment reduces demand for manufacturing labor and nominal manufacturing wages. In addition, higher manufacturing costs under nonattainment raise the price of manufactured goods which further depresses real wages.

In contrast, workers in the nonpolluting nonmanufacturing sector experience smaller decreases in real wages and larger increases in amenities, which results in larger welfare gains. The decrease in real wages is due to two equilibrium forces: the increase in manufactured goods prices, and the decline in nominal wages from the endogenous reallocation of manufacturing workers into the nonmanufacturing sector. Nonmanufacturing workers experience larger amenity gains than manufacturing workers for two reasons. First, nonmanufacturing workers are more likely to originally be located in counties that went into nonattainment and experienced the largest amenity gains. Second, nonmanufacturing workers are more likely to migrate from attainment to nonattainment counties to enjoy improved amenities because nonattainment designations do not directly negatively affect the nonmanufacturing sector.

The welfare effects of the 1997 nonattainment designations are also unequal across space. Gains accrue to a small number of high-population, urban counties that went into nonattainment and experienced improved amenities through reductions in emissions. In these areas, the effect of better amenities dominates the reduction in real wages. Neighboring counties – which may be designated as in attainment and in compliance with the NAAQS – also experienced improved amenities due to avoided atmospheric transportation of pollution. Places farther from urban centers have smaller welfare effects that may be negative due to the combination of lower real wages due to in-migration of manufacturing workers from nonattainment counties and modest improvements in amenities given their substantial distance from nonattainment-induced emissions reductions.

We also take advantage of the quantitative model to simulate the outcomes under a counterfactual policy that never occurred: first-best location-differentiated emissions prices. Implementing first-best emissions pricing would nearly triple welfare gains relative to the 1997 nonattainment designations. The gains are primarily through further improvements in amenities, but emissions pricing also results in smaller negative effects on real wages than the 1997 nonattainment designations.

To highlight the importance of allowing for a spatial dimension in a quantitative model, we simulate the impact of the 1997 nonattainment designations while ignoring the role of economic and physical geography. This is a model-based analogue to an ideal reduced form evaluation of the NAAQS where attainment counties are appropriate counterfactuals for nonattainment counties, and that attainment counties are not affected by nonattainment

through general equilibrium channels or spatial transport of pollution.[6] We find that a model without economic and physical geography understates the aggregate benefits by 75%, incorrectly finds that manufacturing workers are worse off in the aggregate, and misses billions of dollars of gains that accrue to workers in attainment counties.

Finally, we use the model to better understand the specific role of geography in shaping the aggregate impact and distributional consequences of the NAAQS. The gains and losses from labor reallocation in some counties can be substantial and the same order of magnitude as the aggregate effects of regulation. Migration allows workers in the nonpolluting, nonmanufacturing sector to move into nonattainment counties and benefit from the improved air quality. In addition, migration allows workers in the polluting, manufacturing sector to move out of nonattainment counties to places with higher wages. Labor reallocation does impose costs on workers: incumbents in location-sectors with large influxes of labor are worse off from lower nominal wages and higher local consumption good prices. In the aggregate, reallocation of labor across sectors and space has little effect. The reallocation of production through changing trade patterns offsets about a quarter of the regulation-induced decline in consumption. There is less variation in the effects of trade reallocation across counties compared to labor reallocation since the welfare impact of changing wages and goods prices tend to be dominated by the change in the amenity value of pollution. Accounting for cross-county transportation of pollution explains the majority of the aggregate difference in welfare gains in a model with geography versus one without. Mitigating cross-county pollution is a significant component of the total amenity improvement and ignoring how emissions reductions in one state reduces ambient pollution in another leads to an underestimate of nonattainment benefits. These results highlight the importance of accounting for both economic and physical processes when evaluating environmental policy.

Our paper contributes to three main areas of research. First, our work is related to the recent literature using economic geography models to examine the consequences 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 the impact of environmental regulation. We combine a benchmark economic geography model with a workhorse air pollution integrated assessment model which allows us to capture endogenous changes in emissions and how this translates into changes in local amenities. Our work is most closely related to Aldeco, Barrage and Turner (2019), who study the global impact of particulate emissions and the equilibrium

[6]However, our quantitative results show that attainment counties are not proper counterfactuals for nonattainment counties because they experience spillover effects from nonattainment, violating the Stable Unit Treatment Value Assumption.

efficacy of policy responses.[7] Our finding that welfare gains are concentrated around a few major cities 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).[8]

Second, we contribute to the literature on the impact of environmental regulation and, more specifically, the Clean Air Act and 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).[9]

Our paper provides a connection between these two strands of the literature. We develop a nationwide economic geography model that accounts for the direct costs and benefits of the NAAQS targeted by partial equilibrium analyses, as well as equilibrium adjustments in response to improved amenities and lower wages. This allows us to provide a comprehensive, spatially detailed, and internally consistent evaluation of the NAAQS. We find that equilibrium responses and geography captured by our model-based approach are critical for understanding the distribution of welfare impacts. Ignoring these features overestimates costs to workers in regulated industries, misses pecuniary costs imposed on workers in unregulated sectors, and underestimates spillover benefits to workers in attainment counties.

We also contribute to research emphasizing general equilibrium responses to environmental policy. This literature examines the efficiency and incidence of different 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 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.[10] We complement

[7] In a related line of work, Larson, Liu and Yezer (2012) and Colas and Morehouse (2022) use spatial urban models linked to models of energy demand to explore the implications of transportation policy and land use for energy consumption and greenhouse gas pollution.

[8] See Kyriakopoulou (2021) for a review of the literature on the impact of air pollution in cities.

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

[10] 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

this work by focusing on the spatial and sectoral impact of the primary air pollution regulation in the United States as well as the first-best emissions pricing policy.

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 describes the theoretical framework. Section 4 discusses the data. Section 5 describes our empirical strategy and the estimation results for the direct effects of nonattainment designations on emissions. Section 6 presents the quantitative 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 the economic impact of the Clean Air Act in recent decades.

The main air pollution regulations under the Clean Air Act are the National Ambient Air Quality Standards (NAAQS) introduced as part of the 1970 amendments. The original NAAQS set federal standards on ambient concentrations for 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. After a county is given a 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).

(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.

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 plants to move to counties that were historically in attainment (Henderson, 1996; Becker and Henderson, 2000). This suggests an important role 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 heightened regulatory scrutiny following 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 in 1991 (United States Federal Register, 1993). We take this timing into account in our empirical analysis.

3 Model

In this section, we develop a Ricardian model of interregional trade for the United States in the spirit of Eaton and Kortum (2002).[11] In the model there are N locations indexed by i, j as subscripts, K sectors indexed by k, l as superscripts, and P pollutants indexed by p as superscripts. When necessary for clarity in expressions with summations, we introduce a third set of indices to be summed over: n for locations, m for sectors, and q for pollutants.

To quantify the model we use the approximately 3,000 US counties as locations and two sectors – polluting (manufacturing) and nonpolluting (nonmanufacturing) – that are defined in Section 4.3 below. We allow for nonemployment to capture potential permanent transitions out of work. Firms use labor, capital, and emissions as inputs to a Cobb-Douglas production function. This production structure is isomorphic to one in which the firm uses a 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).

Emissions are not traded in markets, but firms face a shadow cost on emissions imposed by

[11] 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).

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 the regulatory shadow price of emissions across counties and sectors affect the allocation of labor and emissions and, hence, the spatial and sectoral distribution of economic activity. Nonattainment designations affect the regulatory shadow price of emissions in the polluting sector.

A key assumption in our model is that nonattainment designations are taken to be exogenous and permanent. This is primarily because of tractability and data availability. Nonattainment thresholds are relatively complicated and difficult to represent within the model. 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, while the AP3 model restricts us to translating emissions into averages. The exogeneity assumption precludes us from capturing two types of potentially endogenous changes to nonattainment. The first is emissions leaking to other counties, increasing these counties' pollutant concentrations and putting them into nonattainment. As we show later we find leakage is relatively small and actually goes in the opposite direction, given our model structure and calibration. The second is nonattainment-induced emissions reductions bringing a county back into attainment. Appendix Figure E1 provides evidence that most counties remain in nonattainment for several years. For example, after the 1990 amendments, more than half of counties newly in nonattainment were still in nonattainment in 2001, indicating that nonattainment is often long-lasting.

3.1 Households

There is a mass L_j^l of households in each location j and sector l where the total number of households is $L = \sum_{j=1}^{N} \sum_{l=0}^{K} L_j^l$. We call (j, l) location-sector pairs *markets*. Households in each market (j, l) maximize a Cobb-Douglas utility function by choosing a single market (i, k) to work and live, potentially choosing to be nonemployed ($k = 0$):

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

Households in (i, k) consume a local final sectoral good, C_i^{km}, from sector m. The parameter α^m is the consumption share of sector m where $\sum_{m=1}^{K} \alpha^m = 1$. $\delta_{ji}^{lk} \in (0, 1]$ is the cost of moving from market (j, l) to market (i, k) in consumption terms and B_i^k captures amenities in location i for sector k workers. The price index in county i for the aggregate Cobb-Douglas

bundle of final sectoral goods is given by:

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

where P_i^m is the price index of goods purchased from sector m 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:[12]

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

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 $\boldsymbol{e} = (e_1^1, \ldots, e_N^1, e_1^2, \ldots, e_N^2, \ldots, e_1^P, \ldots, e_N^P)$ is a vector of emissions e_j^p of pollutant $p = 1, \ldots, P$ in location $j = 1, \ldots, N$.[13] 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 the function 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.[14] 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, significantly increasing concentrations near St. Louis but essentially having no effect

[12] Home production can be thought of as nonemployment benefits. Here we model it as a consumption utility payoff for simplicity following Caliendo et al. (2019).

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

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

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.[15] ,[16] 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 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 pollutant p emitted in county j on one worker in county i in dollar terms as $md_{ij}^p \coloneqq \frac{\partial d_i}{\partial e_j^p} = \frac{\partial D(a_i)}{\partial a_i}\frac{\partial A_i(\boldsymbol{e})}{\partial e_j^p}$. We translate monetized damages into consumption-equivalent terms by expressing damages as a fraction of real wages or home production. Specifically, amenities are given by:

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

where $\bar{B}_i$ is the baseline level of amenities in the absence of pollution, the second term captures the reduction in amenities caused by pollution, and we assume that the marginal damage term md_{in}^p is constant.

Since we do not observe home production $b_i = V_i^0$, we assign V_i^0 to be the population-

[15]The county-specific concentration-damage relationship in AP3 is a function of baseline mortality rates, an age-specific dose-response parameter that multiplicatively maps changes in pollution to changes into age-specific mortality, and the change in pollution. We model prime aged workers in this paper. We allow for workers to have a different baseline mortality rate depending on the county they live in (e.g., because of heterogeneity in healthcare quality), but we assume workers have a common pollution dose-response that is representative of the national age distribution of prime aged individuals in United States in 1997. We obtain data to construct the national distribution from the 1997 Surveillance, Epidemiology, and End Results population dataset. We obtain data on county-specific mortality rates of prime aged individuals in 1997 from the Centers for Disease Control and Prevention's Wonder database. Our approach abstracts away from how age heterogeneity across counties may generate heterogeneity in the pollution dose-response and how the distribution of different ages across counties may change in response to changes in pollution.

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

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,l) to (i,k) incurs a utility cost $\delta_{ji}^{lk} \in (0,1]$ where $\delta_{jj}^{ll} = 1$ for all $j = 1,\ldots,N$ and $l = 0,\ldots,K$.[17] Moving costs have a deterministic component $\bar{\delta}_{ji}^{lk}$ and an idiosyncratic random component ε:

$$\delta_{ji}^{lk} = \bar{\delta}_{ji}^{lk}\varepsilon$$

where ε is drawn from a Fréchet distribution with shape parameter ι:

$$F(\varepsilon) = \exp\left(-z^{-\iota}\right). \tag{3}$$

Larger values of ι imply less dispersion in the distribution of idiosyncratic shocks that households face when considering different mobility options. Given the Fréchet distribution for ε, the share of households that move from (j,l) to (i,k) is:

$$\pi_{ji}^{lk} = \frac{\left(V_i^k B_i^k \bar{\delta}_{ji}^{lk}\right)^{\iota}}{\sum_{n=1}^{N}\sum_{m=1}^{K}\left(V_n^m B_n^m \bar{\delta}_{jn}^{lm}\right)^{\iota}}. \tag{4}$$

A household is more likely to move from (j,l) to (i,k) if (i,k) has higher indirect utility from consumption and amenities after accounting for moving costs, relative to all other locations. The value of consumption and amenities in each location will be determined by the endogenous reallocation of labor and emissions across space. Notice that the denominator is constant across all potential destinations for origin (j,l), and that then ι can be interpreted as a migration elasticity that tells us how responsive migration is to a one percent change in destination (i,k)'s real wage and amenities payoffs, net of bilateral moving costs.

We note two important features of our mobility model. First, its structure captures endogenous "permanent" changes to location and sectoral employment. A larger ι means migration is more elastic with respect to real wages or amenities, consistent with a longer time horizon implicit in our model. Second, it does not capture the option for households to live in a different location from where they work. This commuting choice problem, standard in the quantitative urban literature, would provide another margin for households to adjust to changes in pollution and nonattainment designations.

In Section B of the appendix, we use a version of equation (4) 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

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

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 impact of nonattainment on pollution. 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. improved foliage and visibility 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 estimate is noisy but larger than our quantitative results for amenity improvements.

3.2 Production

Intermediates Competitive intermediate firms use a constant returns to scale Cobb-Douglas technology to produce 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 $\omega \in [0,1]$ denotes different sector k varieties,[18] $p = 1, \ldots, P$ indexes different pollutants, $\gamma \in [0,1]$ is the labor share of value added, $1-\gamma$ is the capital share of value added, $z_i^k(\omega)$ is the productivity of variety ω, and capital is perfectly mobile across space and sectors. The parameter ξ^{kp} is the sector-specific elasticity for pollutant p which is zero for nonpolluting sectors. For the polluting sectors, one unit of output generates one unit of emissions subject to the appropriate normalization of units.[19] To simplify the exposition, going forward we omit ω from the notation whenever the mathematics remain clear.

Emissions from Polluting Intermediate Production In equilibrium, expenditures by intermediate firms on emissions are a constant share of revenues, $\eta_i^{kp} e_i^{kp}(\omega) = \xi^{kp} p_i^k(\omega) q_i^k(\omega)$, which we can rearrange to get an expression for equilibrium emissions intensity per unit of

[18] Varieties can be thought of as particular kinds of differentiated sectoral goods, while the final sectoral good used for consumption (described below) is a bundle of these goods.

[19] $e_i^{kp}/q_i^k = 1$ 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:

$$\frac{e_i^{kp}(\omega)}{q_i^k(\omega)} = \frac{\xi^{kp} p_i^k(\omega)}{\eta_i^{kp}} \tag{5}$$

where $p_i^k(\omega)$ is the price of variety ω, and η_i^{kp} is the exogenously given regulatory shadow price of emissions faced by firms for pollutant p.[20] 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.

Local Sectoral Final Goods A local sectoral final good in location-sector (i, k) is produced as a constant elasticity of substitution aggregate of intermediate sectoral varieties sourced from all locations with elasticity of substitution σ^k:

$$Q_i^k = \left[\int_0^1 \left[\tilde{q}_i^k(\omega)\right]^{\frac{\sigma^k - 1}{\sigma^k}} d\omega\right]^{\frac{\sigma^k}{\sigma^k - 1}}$$

where $\tilde{q}_i^k(\omega)$ is the quantity of variety ω demanded by the final good producer in location-sector (i, k). The local sectoral aggregate is only used for local consumption so that $C_i^k = Q_i^k$.[21]

Productivity of Intermediate Producers For each market, $z_i^k(\omega)$ is the productivity or efficiency of ω, so that productivity varies across producers within a market. Following

[20] Dropping variety notation, we could alternatively have obtained this expression by equating the marginal revenue product of emissions of some pollutant $\tilde{p}$ to its marginal cost (regulatory shadow price): $p_i^k z_i^k \xi^{k\tilde{p}} \left(e_i^{k\tilde{p}}\right)^{\xi^{k\tilde{p}} - 1} \left[\prod_{p \neq \tilde{p}}^P \left(e_i^{kp}\right)^{\xi^{kp}}\right] \left[(K_i^k)^{1-\gamma} (L_i^k)^\gamma\right]^{1 - \sum_{p=1}^P \xi^{kp}} = \eta_i^{k\tilde{p}}$, and then multiplying by $e_i^{k\tilde{p}}$. This alternative expression is convenient because it is also the firm's optimality condition for abatement. This makes clear that the marginal abatement cost is just the forgone marginal revenue product of emissions, and the marginal benefit of abatement is the avoided regulatory shadow price.

[21] Note that the aggregate is composed of goods procured from all locations so the aggregate only being used for local consumption does not imply there is no trade.

Eaton and Kortum (2002), we assume that $z_i^k(\omega)$ takes on a Fréchet distribution:

$$F_i^k(z) = \exp\left(-T_i^k z^{-\theta^k}\right) \tag{6}$$

where the shape parameter $\theta^k > 1$ is the trade elasticity common across all counties and measures the level heterogeneity in productivity. Smaller values of θ^k generate more dispersion, more heterogeneity in productivity, 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 Prices, Trade, and Market Clearing

The unit price of an input bundle for intermediate firms in market (i,k) is:

$$c_i^k = \Omega\left[\prod_{p=1}^{P}\left(\eta_i^{kp}\right)^{\xi^{kp}}\right]\left[(r_i^k)^{1-\gamma}(w_i^k)^{\gamma}\right]^{1-\sum_{p=1}^{P}\xi^{kp}}, \tag{7}$$

where Ω is a constant, r_i^k is the capital rental rate and the assumption of perfect capital mobility implies that $r_i^k = r$ in all markets (i,k). The cost of producing one unit of intermediate variety ω is then $c_i^k/z_i^k(\omega)$.

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 $\tau_{jj}^l = 1$ for all j,l. The final goods producer in market (i,k) procures each variety ω from the cheapest source across all origin counties, inclusive of trade costs:

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

The Fréchet distribution assumption for productivity gives us that the price index of the final sectoral good is:

$$P_i^k = \kappa_1\left(\sum_{n=1}^{N} T_n^k\left[c_n^k\tau_{in}^k\right]^{-\theta^k}\right)^{-1/\theta^k} \tag{8}$$

where κs will denote constants. 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. Intuitively, the more productive sellers are (T_n^k), the lower their input bundle costs are (c_n^k), or the lower the trade barriers are (τ_{in}^k), the greater access consumers in i have to cheaper

products. Bilateral trade flows of sector k goods from j to i is labeled X_{ij}^k and is given by:

$$X_{ij}^k = \kappa_2 T_j^k X_i^k \left[\frac{c_j^k \tau_{ij}^k}{P_i^k}\right]^{-\theta^k} = \kappa_2 T_j^k X_i^k \frac{\left[c_j^k \tau_{ij}^k\right]^{-\theta^k}}{CMA_i^k} \tag{9}$$

where X_i^k is location i's total expenditures on sector k goods. Let Y_j^k denote total income in market (j,k). Summing equation (9) over destinations i and recognizing that the left-hand side is then income in market (j,k) gives:

$$Y_j^k = \sum_{i=1}^{N} X_{ij}^k = \kappa_2 \left[c_j^k\right]^{-\theta^k} T_j^k \underbrace{\sum_{i=1}^{N} \frac{\left[\tau_{ij}^k\right]^{-\theta^k}}{CMA_i^k} X_i^k}_{FMA_j^k} \tag{10}$$

where the last term, labeled FMA_j^k, is firm market access. Firm market access is analogous to consumer market access and captures firms' access to markets with larger buyers (X_i^k), lower trade barriers (τ_{ij}^k), and less stiff competition from other sellers (CMA_i^k). Substituting equation (10) into equation (8) allows us to express consumer market access as a function of firm market access:

$$CMA_i^k = \kappa_3 \sum_{j=1}^{N} \frac{\left(\tau_{ij}^k\right)^{-\theta^k}}{FMA_j^k} Y_k^j. \tag{11}$$

These definitions of market access will play a key role in our market access-based approach to solving the quantitative model (Donaldson and Hornbeck, 2016).

We define trade shares as the fraction of i's sector k expenditures on j which takes on a gravity structure:

$$\lambda_{ij}^k = \frac{T_j^k \left(c_j^k \tau_{ij}^k\right)^{-\theta^k}}{\sum_{n=1}^{N} T_n^k \left(c_j^k \tau_{in}^k\right)^{-\theta^k}}. \tag{12}$$

where i spends more on sector k goods from j if j is more productive, has lower input costs, or has lower trade barriers relative to all other counties. Equation (12) also illustrates the role of the trade elasticity. A larger θ^k amplifies the role of trade costs and input costs – such as nonattainment designations – relative to productivity in determining trade flows.

Finally, market clearing requires that labor income in (i,k) is the labor share of total

expenditures on (i, k) goods:

$$w_i^k L_i^k = \gamma \left(1 - \sum_{p=1}^{P} \xi^{kp}\right) \sum_{n=1}^{N} X_{ni}^k. \tag{13}$$

Equilibrium Definition: Given model primitives T_i^k, $\bar{B}_i$, τ_{ij}^k, $\bar{\delta}_{ij}^{kl}$, N_i, $\bar{\eta}_i^{kp}$, and β_η^p, 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 $i = 1, \ldots, N$, $j = 1, \ldots, N$, $k = 1, \ldots, K$, $l = 1, \ldots, K$, and $p = 1, \ldots, P$ such that equations (4) through (13) are satisfied.

4 Data

The data for the empirical analysis and quantitative exercises include information on nonattainment status and emissions, the wage bill, employment by sector and total nonemployment, and geographic and sectoral mobility. We also use new data on trade costs via the highway network to calculate market access for the quantitative simulations. We collect this information for US counties with consistently defined geographic boundaries over our sample period. Data for our quantitative simulations all correspond 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 in 1990 and between 1996 and 2001. The gap reflects the years in which NEI data are not available. In Appendix D, we use shorter panels to examine 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 power plants emit a wide range of criteria pollutant precursors, but are a primary focus of the the Acid Rain Program – another 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 mobility 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 et al. (2019) and Rudik et al. (2021) – from annual averages between 1995 and 1999. 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

To capture spatial linkages between counties due to interregional trade, we use a measure of trade costs constructed following the approach in Combes and Lafourcade (2005). We first find the routes with the shortest travel times between all county pairs in 1980, 1990, and 2000 via the highway network. To do this we combine newly digitized shapefiles of the US highway network in 1980 and 1990 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. See Appendix A for more detail regarding the use of the highway shapefiles.

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 costs 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.

5 The Effect of Nonattainment on Emissions

The model in Section 3 allows us to estimate the impact of nonattainment on the local regulatory shadow price of emissions in an internally consistent way. To start, we use equation (5) together with the labor share of firm revenues to obtain the following expression:

$$\underbrace{\log\left(\frac{e_i^{kp}}{w_i^k L_i^k}\right)}_{\text{emissions intensity}} = \underbrace{-\beta_\eta^p N_i}_{\text{nonattainment}} - \underbrace{\log\left(\bar{\eta}_i^{kp}\right)}_{\substack{\text{base regulatory shadow} \\ \text{price of emissions}}} + \underbrace{\log\left(\frac{\xi^{kp}}{\gamma\left(1-\sum_{q=1}^{P}\xi^{kq}\right)}\right)}_{\text{emissions elasticities}} \tag{14}$$

where the dependent variable is emissions intensity, i.e., emissions divided by the wage bill. On the right-hand side, the first term captures the effect of nonattainment status on the regulatory shadow price of emissions, the second term is the base regulatory shadow price of emissions in the absence of a nonattainment designation, and the third term includes emissions elasticities and the labor share.

We estimate difference-in-difference specifications that exploit county-level variation in the change in nonattainment status due to the 1990 amendments to the Clean Air Act.[22]

[22]More specifically, we estimate two-way fixed effects models, which are equivalent to a difference-in-difference

Our preferred approach is to use a 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.[23] We estimate specifications of the form:

$$\log\left(\frac{e^p_{i,t}}{w_{i,t}L_{i,t}}\right) = -\beta^p_\eta N_{i,t} + \psi_i + \nu^p_t + \varepsilon^p_{i,t} \tag{15}$$

where t indexes time to reflect the panel structure of our data. The coefficient of interest is β^p_η, which captures the direct effect of nonattainment status under the NAAQS on the price of emissions. In addition, we include 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 state level.

The main threat to identification is from potential non-random assignment of nonattainment status, i.e., counties enter nonattainment due to factors that affect the regulatory shadow price of emissions, are correlated with the emissions intensity, and only imperfectly captured by county and pollutant-year fixed effects.[24] To address this concern we follow the previous literature by focusing on the quasi-experimental assignment of nonattainment status caused by the 1990 CAA amendments (Grainger, 2012; Walker, 2013; Bento et al., 2015). In this setting, the identifying variation for the effect of nonattainment status comes from comparing emissions in attainment and nonattainment counties, before and after a new nonattainment designation under the 1990 amendments.[25]

Table 1 reports our estimates based on equation (15) using Poisson pseudo maximum likelihood (PPML) to address the fact that about a fifth of our county-year-pollutant observations have zero emissions. 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

specifications when treatment timing is not staggered. In our setting, all treated (nonattainment) counties newly enter nonattainment during the NEI report gap from 1991 to 1995 and are considered to be treated thereafter.

[23] We also consider specifications that estimate the combined effect across all pollutants.

[24] For example, if emissions increase because of a change in another regulation that makes polluting more attractive, firms may emit more intensively and cross the nonattainment threshold, causing nonattainment. The 1990 CAAAs generate an exogenous shock to the regulatory shadow prices of emissions which allows us to estimate the parameters of interest.

[25] By focusing on emissions intensity rather than the level of emissions we also circumvent SUTVA issues that may arise due to reallocation. Emissions intensity is only a function of the regulatory shadow price of emissions and production function parameters while the level of emissions depends on other endogenous variables, such as wages, which are affected by nonattainment status in all counties. This can be seen in equations (9) and (13) where wages depend on bilateral expenditures everywhere, which depends on unit input costs (and thus nonattainment) everywhere.

outcome. Columns 3 and 4 instead use emissions intensity, consistent with the model.[26] The results across all four columns are highly consistent. The emissions intensity specifications indicate that nonattainment raises the regulatory shadow price of emissions by 60 percent.

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 highlight the heterogeneity in the effects of nonattainment on emissions of different pollutants: the price of emissions on ammonia goes up five-fold, the price of fine particulates doubles, the price of volatile organic compounds goes up 75 percent, and the prices of nitrogen oxides and sulfur dioxide go up 50 percent.

6 Results

In this section, we simulate counterfactual scenarios using the quantitative model. The values for model parameters are summarized in Table 2. The β_η^p terms are taken from our newly estimated effects of nonattainment on the regulatory shadow price of emissions from Column 4 of Panel B of Table 1. The consumption share parameters and labor share of value added parameter can be obtained from expenditure data. We follow Rudik et al. (2021) for and obtain the consumption share using data from the World Input-Output database for the United States, and we obtain the labor share of value added using value added data from the Bureau of Labor Statistics. We calibrate the remaining model parameters to values estimated elsewhere in the literature. Estimating the trade elasticity in a model-consistent way would require bilateral county trade flows which we do not observe. We circumvent this by taking the value from Simonovska and Waugh (2014). We calibrate the manufacturing pollution elasticities to the values estimated in Shapiro and Walker (2018), which uses administrative plant-level data and a similar model-based approach to how we estimate our β_η^p parameter. Finally we calibrate the migration elasticity to the value in Jaworski et al. (2023). We test the robustness of our results to different parameter values in Section D.

We quantify steady state welfare impacts for several policies relative to a counterfactual steady state where no counties are in nonattainment. First, we consider the welfare impact of the 1997 nonattainment designations shown in Figure 2. Second, we consider the welfare impact of the same 1997 nonattainment designations, but removing economic and physical geography from our model. Specifically, we remove physical geography by zeroing-out the transportation of pollution across county borders in the AP3 atmospheric transport

[26] Note that since the estimates are large, the percentage effect is given by $\exp(\beta) - 1$, and the small value approximation of β_η^p is not valid.

model,[27] we remove labor reallocation by holding mobility shares and the distribution of labor fixed between 1997 nonattainment and no counties in nonattainment, and we remove trade reallocation by holding market access – and thus prices – fixed. These "no geography" results highlight the contribution of using a quantitative model to understand the aggregate and distributional consequences of the NAAQS versus other approaches that do not leverage a model. Third, we quantify the change in welfare from the set of location-differentiated first-best emissions prices.[28] Fourth, we examine the effect of sequentially tightening NAAQS thresholds for determining nonattainment in 1997.

To solve for the equilibrium under each policy (or absence of policy), we first recover the regulatory shadow prices of emissions (η_i^{kp}) and productivity (T_i^k) for each market under the 1997 nonattainment designations using observed data on input costs, emissions, and trade costs, along with the equations governing the model equilibrium. We then use our empirical estimates from Table 1 to obtain the base regulatory shadow price of emissions in the absence of nonattainment for all markets. Once we have productivity and the base regulatory shadow price of emissions, we can then use the equilibrium conditions of the model solve for the new equilibrium without any counties in nonattainment, under any particular set of nonattainment designations, and under the first-best location-differentiated emissions price.[29,30]

Appendix C provides more detail on how we solve for counterfactual outcomes and compute welfare.

We report welfare in consumption-equivalent terms. When reported in percent, welfare for a particular county-sector pair reflects the percent change in real wages that would generate the same welfare impact as the nonattainment shock for incumbent workers in that particular county-sector pair.[31] When aggregating welfare to higher levels than county-sector, we take population-weighted averages. We also report welfare in dollars by translating the percentage effects using local real wages. Welfare in dollar terms therefore does not account for the

[27]The AP3 atmospheric transport model boils down to a source-receptor matrix. We shut down physical geography by zeroing out the off-diagonal elements.

[28]We compute the first-best emission price policy as the spatially differentiated tax equal to the damage caused by a unit of emissions in a county, above the base regulatory shadow price of emissions which captures other regulations besides CAA-induced nonattainment. The tax accounts for how workers may have migrated or changed industries in response to the tax.

[29]We also shock productivity in two of our robustness checks in Table D2.

[30]Note that our model precludes saying anything about transitional dynamics. One other critical assumption is the Cobb-Douglas production technology. This generates a proportional response of emissions intensity to nonattainment designations as made clear in equation (14), however the level of emissions may respond more flexibly.

[31]Thus, a manufacturing worker in Los Angeles County, California who transitions into nonmanufacturing or nonemployment, or who migrates to Harris County, Texas, is counted in the manufacturing welfare for Los Angeles County.

impact on nonemployed workers who do not receive market wages.[32]

6.1 Aggregate Impact

The main aggregate quantitative results are reported in Table 3. Panel A reports the welfare gains associated with the 1997 nonattainment designations relative to no counties being in nonattainment. The first two columns report the total effect; welfare was 0.57 percent ($40 billion) higher due to the actual 1997 nonattainment designations. The remaining columns decompose the total effect by source. There is an increase of 0.66 percent (or $51 billion) due to better amenities and a decrease of 0.08 percent (or $11 billion) due to lost consumption from lower real wages. The second row shows that workers in the polluting, manufacturing sector are better off, but have lower consumption. The third row shows that workers in the nonpolluting, nonmanufacturing sector experience gains of 0.70 percent (or $44 billion) due to larger amenity gains and smaller losses in consumption. The fourth row shows that nonemployed workers are better off because they benefit from improved amenities. The last two rows of the panel show that nonattainment counties obtain most of the benefits, however attainment counties have improvements in both amenities and consumption. Since attainment counties are not directly affected by nonattainment, this result suggests an important role for physical and economic geography in transmitting the effect of nonattainment across counties.

To highlight the benefits of using a quantitative model, Panel B reports the welfare gains associated with the 1997 nonattainment designations relative to no counties in nonattainment, but omit the explicit features of economic and physical geography (i.e., cross-county pollution transport, labor reallocation, and trade reallocation) captured by the baseline model. This panel shows, in the aggregate, an quantification of what is missed if one were to ignore equilibrium adjustments and cross-county pollution transport. The welfare gains from the 1997 nonattainment designations ignoring economic and physical geography are 0.16 percent, under one-third the welfare gain when accounting for geography. Ignoring geography also results in a different distribution of welfare gains across sectors and counties. Across sectors, it gives the opposite sign for the effect on manufacturing welfare, while understating nonmanufacturing gains by half and reporting zero effect of nonattainment on nonmanufacturing consumption. Across county types, it suggests there is zero effect on attainment counties while also understating the benefits to nonattainment counties.

Why does ignoring physical and economic geography matter for measuring the welfare impacts through amenities and consumption? For amenities, omitting physical geography

[32]Percentage and dollar-valued welfare gains may not be consistent in the sense that population-weighted percentage welfare gains may be positive but dollar-valued welfare gains could be zero or negative. This may occur if places that are worse-off have higher real wages than places that are better off.

and the dispersion of pollution underestimates the direct amenity benefits to those outside the county where emissions are reduced, while leaving out economic geography and the ability of workers to reallocate across space misses how workers adjust to take advantage of the non-uniform improvements in amenities. For consumption, omitting economic geography overestimates the declines in real wages for manufacturing workers since it omits how they can move across space to attainment counties or across sectors into nonmanufacturing to maintain higher real wages; for nonmanufacturing workers it omits the increased competition in the labor market from manufacturing workers changing jobs and also omits the increase in consumption good prices as nonattainment increases the costs of manufactured goods. Overall, this shows that incorporating economic and physical geography is important for quantifying the aggregate impact of the Clean Air Act and suggests it will be important understanding its full distributional consequences, which we explore further in Section 6.2.

In Panel C, we consider the effect of imposing an emissions pricing scheme in which the county-specific emissions prices η_i^{kp} are set equal to county-specific marginal damages. The welfare gains are 1.65 percent (or \$111 billion), which are more than twice as large as the benefits stemming from the 1997 nonattainment designations. The gains from improved amenities are substantial at 1.71 percent (or \$117 billion) and are only marginally offset by the negative effects from lower consumption. Notably, manufacturing workers are better off in consumption terms from a policy of county-specific emissions pricing relative to the observed 1997 nonattainment designations.

Next we explore the implications of making the NAAQS thresholds for nonattainment more stringent than their actual levels in 1997. We perform a series of counterfactual experiments where we compute the equilibrium outcomes of the economy if the pollution threshold for putting a county into nonattainment ranged from the actual threshold levels in 1997 down to a level where every county with a pollution monitor would be put into nonattainment. We then compare the outcomes of these simulations to the equilibrium outcome of an economy where no counties are in nonattainment as in the previous results.

Figure 3 reports the results. To start, the points on the far left side give the total welfare gain, amenity welfare gain, and consumption welfare gain of imposing nonattainment designations using the actual thresholds in 1997, relative to no counties in nonattainment. Moving to the right in Figure 3 increases the stringency of the NAAQS concentration thresholds uniformly across all pollutants. The counterfactual pollutant thresholds as a fraction of the actual thresholds is given by the x-axis at the bottom and the number of counties that would be put into nonattainment under these counterfactual thresholds is given by the x-axis at the top. For example, in the middle of the figure, the NAAQS thresholds are set to 50 percent of the actual thresholds (i.e., twice as stringent) which would result

in putting about 550 counties into nonattainment. The points on the far right side indicate thresholds that puts every county with a pollution monitor in nonattainment. Note that this experiment does not force pollution to be zero in the model, but instead simulates that counties adopt technologies and practices mandated by a nonattainment designation.[33]

The points on the far left side reiterate the gains associated with the actual 1997 nonattainment designations reported in Panel A of Table 3: welfare increases by 0.57 percent relative to a counterfactual with no counties in nonattainment, while amenity welfare increases by 0.66 percent and consumption welfare decreases by 0.08 percent. Moving to points farther to the right shows that increasing the stringency of the NAAQS increases welfare until nonattainment thresholds are about one-fifth of their 1997 level. More stringent nonattainment thresholds at one-fifth of the 1997 levels increase welfare by up to 0.17 percentage points (or $12 billion) over the actual thresholds.[34] After this point, additional gains for amenities and losses for consumption are negligible as the marginal nonattainment county becomes increasingly rural and less populated.

Appendix Table D2 examines the sensitivity of these results to alternative values of the trade and migration elasticities, the consumption and labor share parameters, the pollution elasticities, congestion and agglomeration, and allowing for marginal damages to increase in income. The most important parameters for the aggregate quantitative results are the trade and migration elasticities, and the emissions elasticities for the manufacturing sector in particular. Aggregate welfare is always positive for reasonable trade and migration elasticities, and manufacturing welfare is only negative for the highest value of the trade elasticity or if nonattainment induces a significant total factor productivity decline in addition to making emissions more costly to produce. The sign of manufacturing welfare only changes after at least doubling the estimated elasticities from Shapiro and Walker (2018).

6.2 The Spatial Effect of Nonattainment and the Role of Geography

In this section we highlight the spatial distribution of the impacts of the 1997 nonattainment designations, as well as how geography shapes the impact of nonattainment designations. The geography results provide an evaluation of how reallocation can help workers adjust to the costs and benefits of the NAAQS, but also illustrate the potential errors in quantifying

[33]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.

[34]Another framing of this result is that a severe tightening of the thresholds only improved upon the actual thresholds by a fifth (0.74% welfare gains versus 0.57% welfare gains).

welfare effects using approaches that cannot capture these features.

6.2.1 The Spatial Effect of Nonattainment

Figure 4 shows the spatial distribution of the welfare impacts of 1997 nonattainment designations across all counties in our sample.[35] The areas in blue experience welfare gains while areas that experience losses are shown in red. The map reveals substantial heterogeneity 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.

Figure 5 decomposes the welfare results along two margins. The top panels show the welfare impact on manufacturing and nonmanufacturing workers. Manufacturing workers are marginally worse off in most nonattainment counties despite large amenities improvements because nonattainment has large, negative effects on their real wages. In nonattainment counties with large emissions reductions – such as those around Chicago, New Orleans, or St. Louis – the amenity 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 experience amenity 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 results in Figure 4 because nonmanufacturing workers account for a majority of the workforce. Nonmanufacturing workers experience a small negative effect on consumption and large amenity improvements.

The bottom panels show the decomposition of aggregate welfare impact into amenity improvements and changes in consumption and real wages. The bottom left map 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. Highly-populated nonattainment areas, such as St. Louis, Houston, or Los Angeles have the largest amenities improvements. Two factors contribute to this result. The first is that manufacturing activity, in level terms, is heavily concentrated in cities and thus generates large amounts of emissions and ambient pollution in cities.[36] The second is that the majority of nonattainment counties either contain a city or

[35]The model is fundamental for understanding the spatial distribution of welfare since a perfect mobility assumption will ensure that welfare, and thus welfare gains, are uniform across space. In reality, workers face frictions moving across space and sectors, prohibiting equalization of welfare.

[36]Cities like Los Angeles may not be thought of as manufacturing hubs because manufacturing is not be a large share of the local economy in these cities. However, because these cities are large, manufacturing is

are nearby one. So cities, instead of more rural areas, tend to have more emissions reductions themselves and in other nearby counties, and thus the largest amenities improvements even in percentage terms.

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 price of emissions 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 3), raising marginal costs of production, and shrinking manufacturing output and emissions in attainment counties.[37] Negative leakage generally accounts for 0.1–1.0 percent of the aggregate emissions decline, depending on the pollutant.

The bottom right map shows the change in welfare caused by changes in real wages and consumption. Consumption decreases on average in nonattainment counties but increases in most attainment counties due to the increase in nominal wages that also caused negative leakage. Taken together, these maps make clear that the welfare improvements for the largest beneficiaries of the NAAQS are driven by improved amenities.

6.2.2 The Role of Economic and Physical Geography

Figure 6 shows the geography of labor mobility. The top left map 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 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 map shows the welfare value of incumbent workers in these counties being able to change mobility patterns. In the aggregate, labor reallocation has a near-zero aggregate effect, but the map shows that this masks significant heterogeneity. Less populous

large in *level* terms and thus accounts for significant amounts of emissions and local ambient pollution.

[37] For tractability we have assumed Cobb-Douglas production, but the extent of leakage critically depends on the elasticity of substitution between factors in production. If factors are more substitutable, then firms in nonattainment counties will more strongly reallocate from emissions to capital and labor, amplifying the wage and rental rate increases, as well as emissions decreases, in attainment counties. Note that equation (5) shows that emissions intensity in attainment counties does not change even though the level of emissions does because of changes in output.

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. Being able to move improves welfare for these workers by up to a third of a percent. Conversely, highly-populated nonattainment areas, such as St. Louis, Houston, or Los Angeles are worse off from labor reallocation. The amenities improvement in these areas makes incumbent workers better off, but it also makes the location more attractive to outside workers and induces in-migration. This intensifies labor market competition and depresses incumbent real wages which dominates the amenities improvements.[38] These results highlight that ignoring labor reallocation substantially overstates welfare improvements to incumbents in major urban areas where labor market competition intensifies and understates welfare gains elsewhere because workers can move into counties with improved air quality or better wages.

The bottom two maps 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 improved amenities shown in Figure 5. Workers leaving nonattainment counties – primarily in manufacturing – migrate to counties in the Plains and to about 30 nonattainment counties with large amenity improvements.[39] This influx of workers depresses real wages in these areas and leads to the decrease in welfare for incumbent workers shown in Figure 4. This differential movement of manufacturing versus nonmanufacturing workers as well as differences in their initial county of residence, is why nonmanufacturing workers reap larger amenity gains than manufacturing workers. Nonmanufacturing workers are more likely to move to nonattainment counties with improved amenities, while manufacturing worker movement is more split between attainment and nonattainment counties due to the negative manufacturing wage impact of nonattainment. Initially, 66 percent of nonmanufacturing workers are in nonattainment counties compared to 59 percent of manufacturing workers, so even without migration, the aggregate amenity benefits to nonmanufacturing workers may be larger.

In addition to the 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

[38] In our model, there are no ex ante differences in labor quality (e.g., by skill or demographic group). These quantitative results are consistent with a large empirical literature that finds reduced wages in response to in-migration of similar types of labor from international (e.g., Card, 2001; Borjas, 2003) or internal (e.g., Kleemans and Magruder, 2018) migrants across local labor markets.

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

changed jobs and entered the nonmanufacturing sector to get higher real wages, despite costs of switching their sector of employment, with a small share entering nonemployment.

Figure 7 shows the effect of the remaining two aspects of geography, trade in goods and cross-county transport of pollution. The left panel plots the welfare value of being able to adjust to nonattainment through changing trade patterns in response to changes in goods prices. In total, adjustments through trade offset aggregate losses by 0.02 percentage points, which amounts to about a quarter of the aggregate consumption welfare loss. The magnitude of the largest county-specific effects of trade tends to be smaller than for labor reallocation, which is consistent with amenities accounting for the bulk of the impact of nonattainment as previously shown in Table 3, and trade not directly allowing households to adjust to changes in amenities.

The right panel of Figure 7 plots the welfare effect of accounting for physical geography. The map shows the effect of 1997 nonattainment designations in a model accounting for pollution crossing county borders, versus one where this pollution is unaccounted for in welfare calculations and in household mobility decisions. The difference in gains are highest in counties that are nearby major emitter counties.[40] These counties reap significant amenities improvements from large reductions in cross-county pollution externalities under the 1997 nonattainment designations. The vast majority of counties have non-negligible welfare gains. At the median, accounting for physical geography increases a county's welfare by 0.29pp. In the aggregate, physical geography accounts for the majority of the combined welfare difference from capturing economic and physical geography.

Appendix E provides additional geographic results. In particular, we show the impact of accounting for potential congestion and agglomeration externalities, the impact of accounting for potential productivity effects of nonattainment beyond raising emissions costs, and the benefits of the first-best location-specific pricing policy versus the actual set of nonattainment designations. To summarize: (1) accounting for congestion and agglomeration decreases welfare gains in major cities because congestion effects tend to dominate agglomeration effects such that in-migration further reduces welfare for incumbents, (2) negative productivity effects consistent with the reduced form literature or positive productivity effects reflecting the strong version of the Porter hypothesis have small effects in nonattainment counties and smaller spillover effects into attainment counties, and (3) using emissions pricing improves welfare in every county relative to the 1997 nonattainment designations.

[40]These counties may be in nonattainment themselves.

7 Conclusion

In this paper we develop an integrated spatial general equilibrium model to study the impact of environmental regulation. The model 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 model to quantify the aggregate and distributional consequences of National Ambient Air Quality Standards (NAAQS) under the Clean Air Act. We find that the NAAQS delivers net benefits of over $40 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 over $1 trillion.

We use the model to consider counterfactual policies and find that increasing threshold stringency could improve welfare by billions of dollars per year and that further gains are possible through emissions pricing. In addition, we use the model to study the mechanisms underlying 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 shape the response to changes in environmental regulation. Our results indicate that accounting for atmospheric pollution transport and labor reallocation is particularly important for the level and distribution of welfare effects. This emphasizes how analyses that do not account for how regulation induces equilibrium reallocation of pollution and workers – potentially into unregulated areas – may misquantify or entirely mis-sign the effects of environmental regulation for subsets of the population.

A drawback of our approach is that the model is static so that we do not consider the possibility that technological change (or other shocks) reduce the cost of enforcement or compliance over time and we are not able to study the transition between the steady states. In addition, other factors not in our model that may contribute to the welfare impact of environmental regulation include market structure, heterogeneous preferences across households, and nonhomothetic preferences over housing or consumption. We leave these promising directions for future research.

8 Data Availability

Data and code replicating the tables and figures in this article can be found in Hollingsworth et al. (2024) in the Harvard Dataverse, https://doi.org/10.7910/DVN/7PHIGL.

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Table 1: Estimated effect of nonattainment on the regulatory shadow price 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**
	(0.21)	(0.21)	(0.24)	(0.24)
B. By Emitted Pollutant				
Ammonia ($\beta_\eta^{NH_3}$)	1.7***	1.6***	1.7**	1.6**
	(0.38)	(0.39)	(0.75)	(0.76)
Nitrogen Oxides ($\beta_\eta^{NO_x}$)	0.47***	0.50***	0.37**	0.40**
	(0.18)	(0.18)	(0.16)	(0.16)
Fine Particulates ($\beta_\eta^{PM_{2.5}}$)	0.17	0.18	0.66*	0.68*
	(0.18)	(0.18)	(0.36)	(0.35)
Sulfur Dioxide ($\beta_\eta^{SO_2}$)	0.24	0.23	0.43*	0.42
	(0.24)	(0.24)	(0.26)	(0.26)
Volatile Organics (β_η^{VOC})	0.42	0.40	0.59	0.57
	(0.37)	(0.37)	(0.45)	(0.46)
Observations	70,225	70,225	70,225	70,225
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 (15). Each coefficient can be interpreted as a semi-elasticity. 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 convert the emissions outcome variable to the theoretically-consistent emissions intensity relative to labor costs. Robust standard errors clustered at the state level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Parameter values for quantitative model.

Parameter	**Value**
Consumption Share (α)	0.2740
Labor Share (γ)	0.4810
Trade Elasticity (θ)	4.0000
Migration Elasticity (ι)	1.0000
Manufacturing Pollution Elasticities (ξ^p)	
NH_3	0.0023
NO_x	0.0038
$PM_{2.5}$	0.0023
SO_2	0.0028
VOC	0.0068
Effect of Nonattainment on Emissions Prices (β_η^p)	
NH_3	2.3000
NO_x	0.3800
$PM_{2.5}$	0.6800
SO_2	0.4300
VOC	0.5600

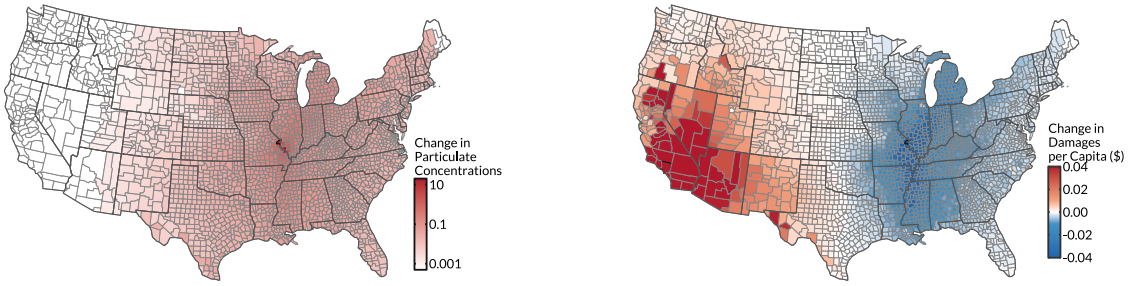
Notes: The consumption share comes from Rudik et al. (2021) and is computed using the United States data from the World Input Output Database. The labor share comes from Bureau of Labor Statistics (2017). The trade elasticity is from Simonovska and Waugh (2014). The migration elasticity is from Jaworski et al. (2023). The pollution elasticities are drawn from Shapiro and Walker (2018). Pollution elasticities for nonmanufacturing are all zero. The effects of nonattainment on the marginal cost of emissions are our preferred estimates from Section 5.

Table 3: Welfare impacts of the 1997 nonattainment designations with and without physical and economic geography, and the welfare impact of implementing first-best emissions pricing.

	Total		Amenity		Consumption	
	%	Billion $	%	Billion $	%	Billion $
A. 1997 Nonattainment						
Aggregate	0.57	40	0.66	51	-0.08	-11
Manufacturing	0.18	0	0.45	7	-0.4	-7
Nonmanufacturing	0.63	40	0.7	44	-0.05	-4
Nonemployed	0.6	-	0.62	-	-	-
Attainment Counties	0.36	10	0.26	6	0.09	4
Nonattainment Counties	0.78	30	1.04	45	-0.25	-15
B. No Economic/Physical Geography						
Aggregate	0.16	10	0.24	22	-0.08	-11
Manufacturing	-0.52	-8	0.17	3	-0.69	-11
Nonmanufacturing	0.26	19	0.26	19	0	0
Nonemployed	0.21	-	0.21	-	-	-
Attainment Counties	0	0	0	0	0	0
Nonattainment Counties	0.32	10	0.48	22	-0.16	-11
C. First-Best Emissions Pricing						
Aggregate	1.65	111	1.71	117	-0.06	-6
Manufacturing	1.21	15	1.15	17	-0.09	-2
Nonmanufacturing	1.7	97	1.79	101	-0.07	-4
Nonemployed	1.77	-	1.76	-	-	-
Attainment Counties	1.52	38	1.46	35	0.05	3
Nonattainment Counties	1.77	73	1.95	82	-0.16	-9

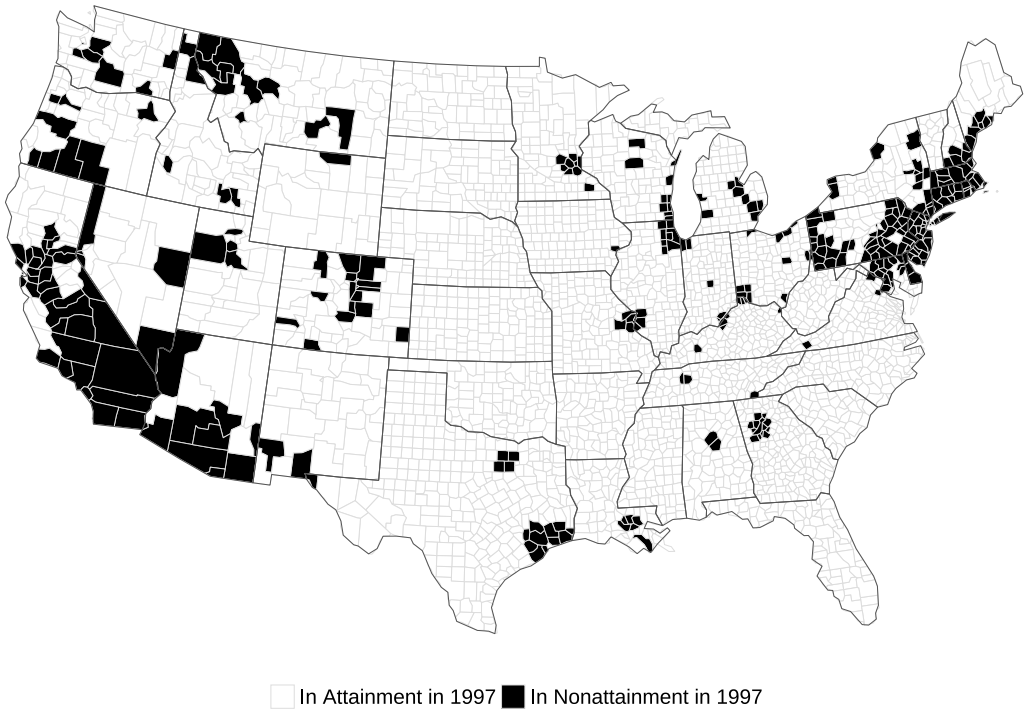
Note: Welfare is computed as the equivalent variation of (A) the observed nonattainment status in 1997, (B) the observed nonattainment status in 1997 if mobility share are held fixed, market access is held fixed, and pollution crossing county borders is ignored, or (C) first-best emissions pricing, relative to a counterfactual in which no counties are in nonattainment or face emissions pricing. The simulations in (A) and (C) account for labor reallocation, trade, and atmospheric transport of pollution. The first-best result sets the optimal location-specific nonnegative emission prices. Numbers may not sum up fully due to rounding.

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



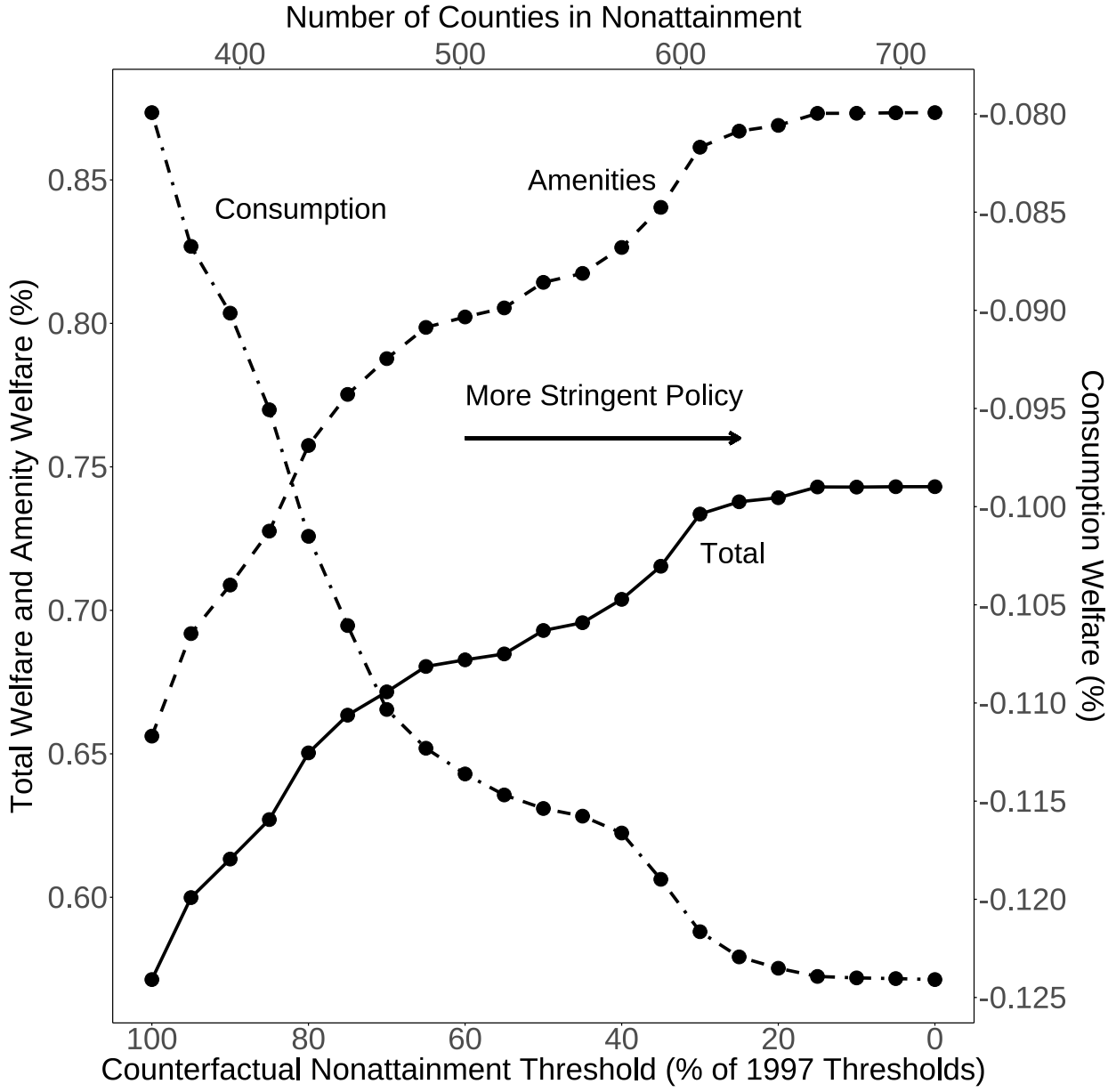
Note: The left map shows changes in $PM_{2.5}$ concentrations caused by one thousand metric tons of nitrogen oxides emissions in St. Louis County, MO. The units for the change in $PM_{2.5}$ is micrograms per cubic meter. The right map shows changes in damages per capita from moving 1000 metric tons of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

Figure 2: Counties in nonattainment in 1997.



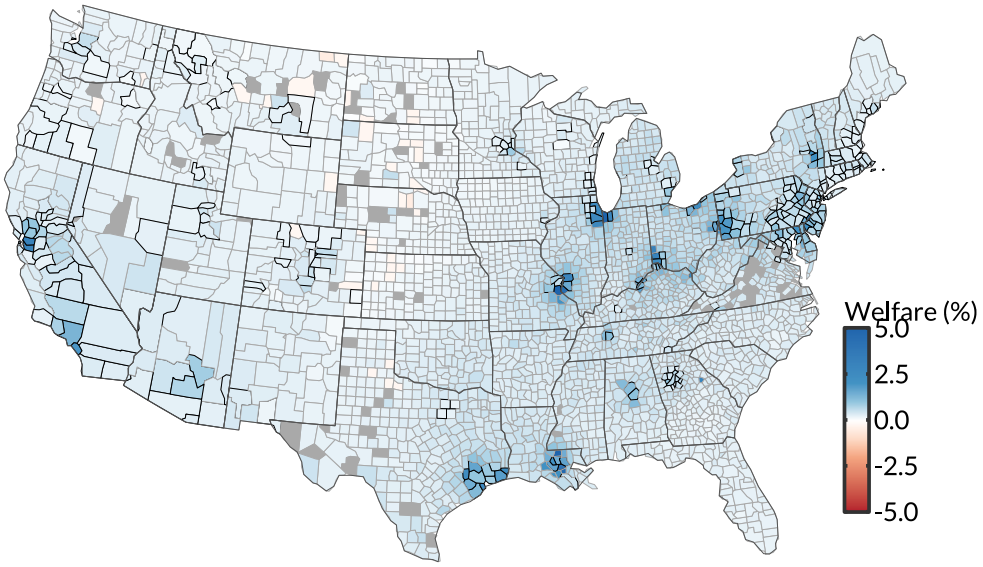
Notes: The map indicates in black all counties in nonattainment in 1997.

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



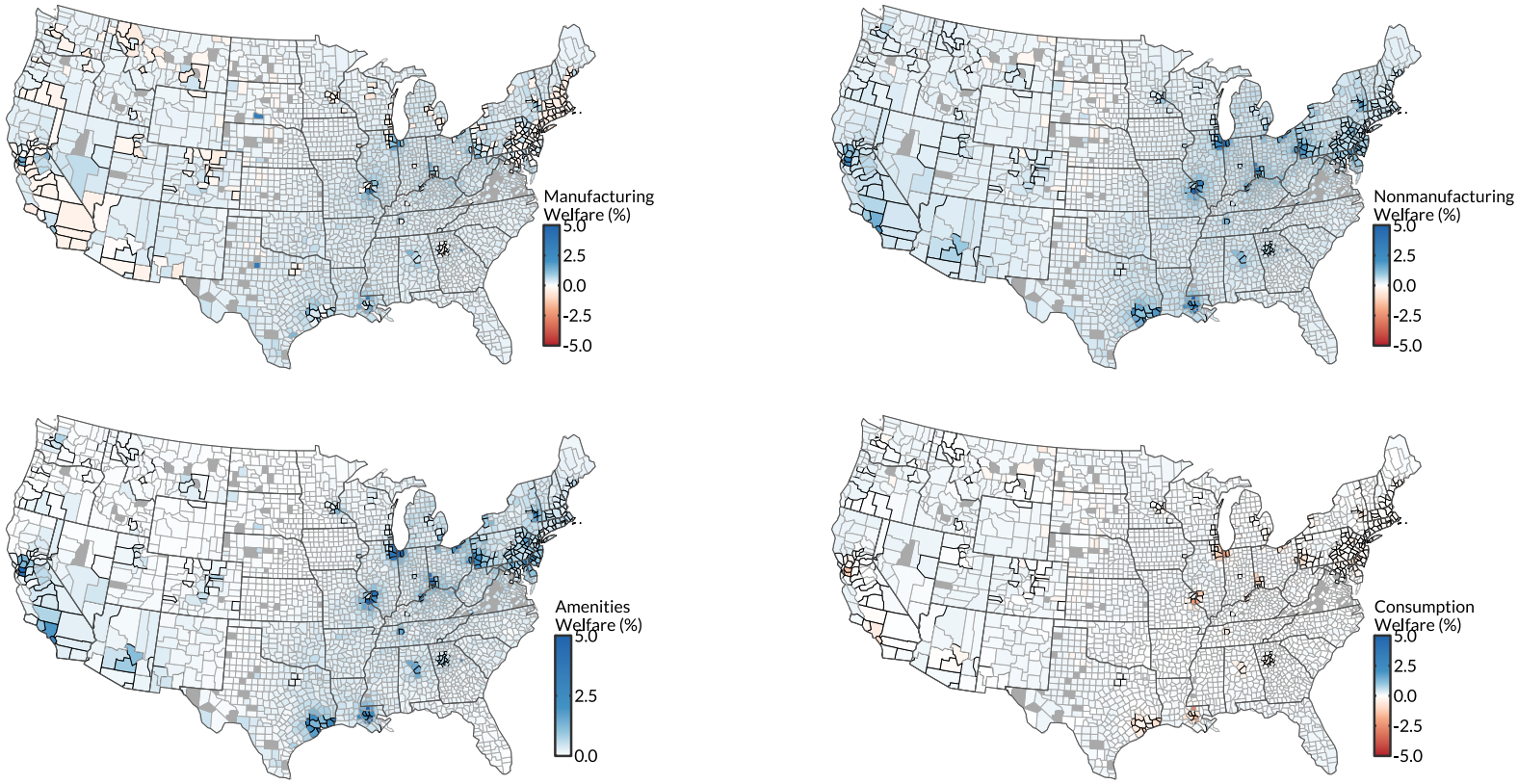
Note: Each point in the figure reports welfare under alternative counterfactual thresholds for nonattainment that range from the actual nonattainment designations (on the left) to every county with a pollution monitor in nonattainment (on the right), relative to the scenario in which no counties are in nonattainment. Welfare is calculated as equivalent variation; it is reported in consumption-equivalent terms. 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 line reports total welfare. The dashed line reports amenity welfare. The dotted 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.

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 to the welfare calculated under a counterfactual scenario in which no counties are in nonattainment. Welfare is calculated as equivalent variation; it is reported in consumption-equivalent terms. 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 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 to the welfare calculated under a counterfactual scenario in which no counties are in nonattainment. Welfare is calculated as equivalent variation; it is reported in consumption-equivalent terms. 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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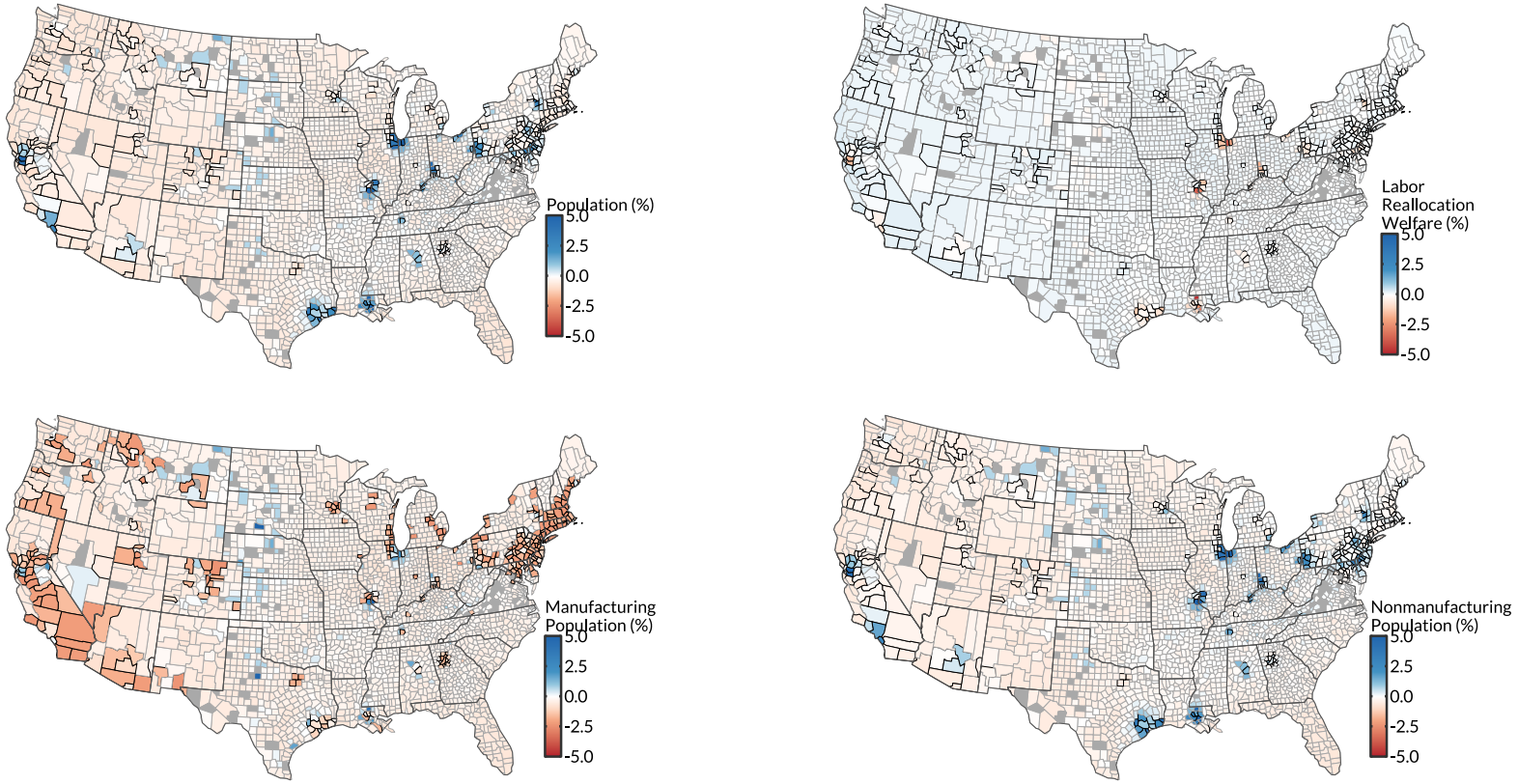
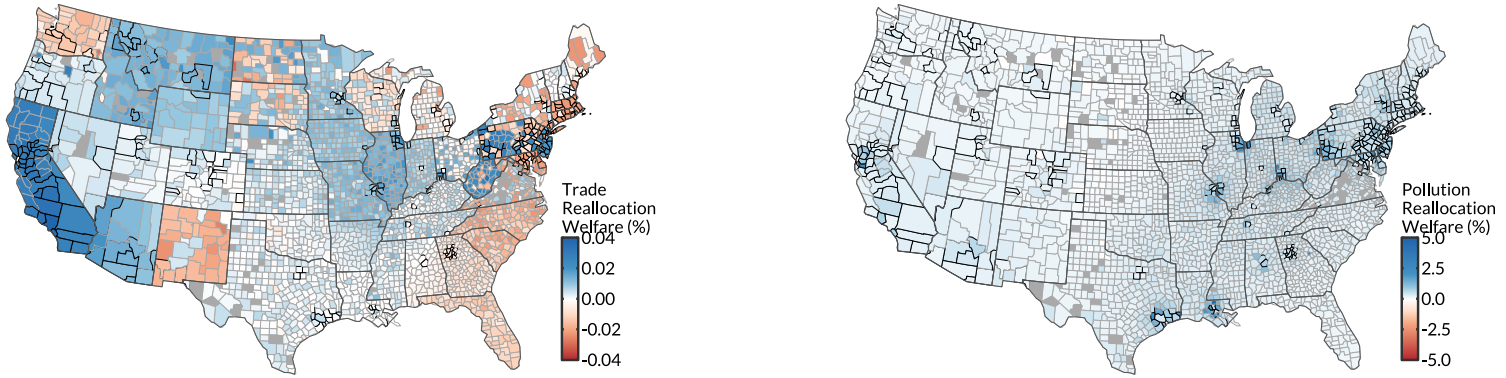
Figure 6: The change in population and welfare from endogenous labor reallocation.



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 to 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 to the welfare calculated under a counterfactual scenario in which no counties are in nonattainment, with free adjustment of mobility shares and the distribution of labor versus holding mobility shares and the distribution of labor fixed at the equilibrium 1997 nonattainment levels. Welfare is calculated as equivalent variation; it is reported in consumption-equivalent terms. 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 7: The change in welfare from trade and accounting for physical geography.



Note: The change in welfare in the left panel is the difference between the welfare calculated by the model using the 1997 nonattainment status provisions relative to the welfare calculated under a counterfactual scenario in which no counties are in nonattainment, with free adjustment of market access versus holding market access fixed at the equilibrium 1997 nonattainment levels. The change in welfare in the right panel is the difference between the welfare calculated by the model using the 1997 nonattainment status provisions relative to the welfare calculated under a counterfactual scenario in which no counties are in nonattainment, accounting for cross-county pollution transport versus not accounting for cross-county pollution transport. Welfare is calculated as equivalent variation; it is reported in consumption-equivalent terms. 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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Online Appendix

Economic Geography and Air Pollution Regulation in the United Statesy

Alex Hollingsworth, Taylor Jaworski, Carl Kitchens, and Ivan Rudik

A Calculating Trade Costs

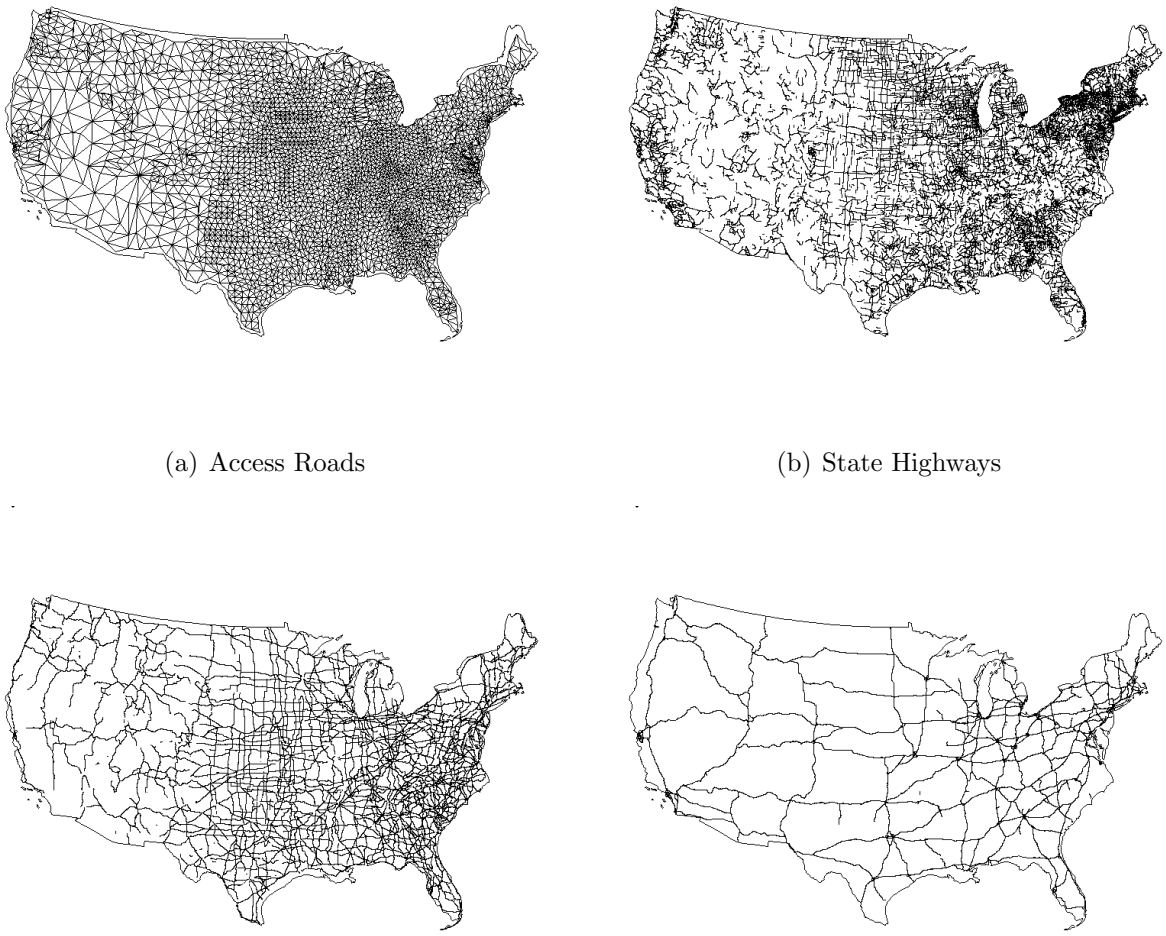
To construct trade costs, we utilize new data on the extent of the highway network in each year.[41] For 2000 and 2010, we use shapefiles maintained by the federal government. Prior to 1994, the federal government did not maintain shapefiles of the highway network, thus, for earlier periods, we construct our own network databases. To do this, we begin with the year 2000 shapefiles. We then overlay scans of the 1990 Rand McNally Road Atlas in ArcGIS, where we then re-code, edit, or delete segments of the 2000 network to generate the 1990 network. We follow this same procedure, overlaying the 1980 Rand McNally Road Atlas on the 1990 shapefiles. Thus, we have a harmonized panel data of the highway network from 1980 to 2010 that includes state highways, US federal highways, and Interstate highways. Additionally, we construct a set of "access" roads between each county centroid and its neighboring county centroid to ensure that all origins and destinations are connected to the network.[42] In Figure A1, Panels (a) through (d), we highlight the different components of the network for 1990.

We assign travel speeds to each type of segment based on its classification, 10 miles per hour (access roads), 35 miles per hour (state highways), 55 miles per hour (US Highways), and 70 miles per hour (Interstate Highways). These speeds are then used to construct the time cost associated with each segment. We represent each county in space by its geographic centroid and compute the minimum travel time through the network for each origin-destination pair using Dijkstra's Algorithm. For each route, we compute the travel time and distance traversed. Following Combes and Lafourcade (2005), we construct τ_{ij} by monetizing the travel time and distance using the hourly wage of a truck driver and national fuel prices for that year and fuel efficiency of a truck in the given year and normalizing by the average value of a shipment in the 2012 commodity flow survey. To construct market access, we then solve the system of equations outlined in Section 4.

[41] For our period of study we focus on trade costs via the highway network given that truck-only transportation accounted for more than 80 percent of the value of domestic trade (excluding the movement of parcels by the United States Post Office or by courier) according to the Commodity Flow Survey in 2002.

[42] Jaworski and Kitchens (2019) show that the choice of geographic or population-weighted centroid makes little difference empirically.

Figure A1: Components of Highway Network.



(a) Access Roads

(b) State Highways

(c) US Highways

(d) Interstate Highway System

Note: The figure shows the four components of the US highway network used to calculate travel time and trade costs. Panel (a) shows the access road network with an assigned speed of 10 miles per hour, Panel (b) shows the state highway network with an assigned speed of 35 miles per hour, Panel (c) shows the US highway network with an assigned speed of 55 miles per hour, and Panel (d) shows the Interstate Highway System with an assigned speed of 70 miles per hour.

B Amenities in Reduced Form

In the quantitative model we 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 regulatory shadow price of emissions η_i^{kp} in the main text:

$$B_i = \bar{B}_i \exp\left(\beta_B N_{i,t}\right). \tag{16}$$

$\bar{B}_i$ 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. $\beta_{\mathbf{B}}$ can be interpreted as the percent change in amenity-related welfare from imposing nonattainment.

We obtain our equation of interest by manipulating equation (4) 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:

$$\log\left(\frac{\pi_{ij}}{\pi_{ii}}\right) = \beta_B\left(N_j - N_i\right) + \log(\bar{B}_j/\bar{B}_i) + \log\left(\frac{w_j/P_j}{w_i/P_i}\right) + \log(\delta_{ij}). \tag{17}$$

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.

Assuming amenities are common across workers in both sectors, we use a difference-in-differences approach:

$$\log\left(\frac{\pi_{ij,t}}{\pi_{ii,t}}\right) = \beta_B\left(N_{j,t} - N_{i,t}\right) + \log\left(\frac{w_j/P_j}{w_i/P_i}\right) + \phi_{ij} + \nu_t + \varepsilon_{ij,t} \tag{18}$$

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 quantitative 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. We note that this is a rough test since the IRS data do not report wages, and so we must use county average real wages as an alternative.

B.1 The Effect of Nonattainment on Amenities

Table B1 shows the results from estimating models building up to our preferred specification in equation (18). 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 2.3 percent. 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 relatively noisy estimates that nonattainment status improves utility between about 1.5 and 2.5 percent, holding real wages fixed. This is slightly larger than the amenities estimates from our model as hypothesized.

Table B1: Difference-in-differences estimates of the effect of nonattainment on local amenities.

	(1)	(2)	(3)
1(Dest. Nonattainment) - 1(Orig. Nonattainment)	0.023	0.014	
	(0.017)	(0.015)	
1(Destination Nonattainment)			0.015
			(0.015)
1(Origin Nonattainment)			−0.014
			(0.015)
Observations	1,048,420	1,048,420	1,048,420
Origin-Destination FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Real Wage	Omitted	Coef. Fixed	Coef. Fixed
Origin vs Destination	Fixed	Fixed	Free

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

Robust standard errors are clustered two ways at the origin state and destination state levels.

C Simulating Counterfactuals

C.1 Solution Algorithm

To simulate our counterfactual we first need to invert the model and solve for the level of productivity T_i^k and the regulatory shadow price of emissions η_i^{kp}. We will not need to solve for the level of amenities B_i^k since observed mobility shares are effectively sufficient statistics for the composition of moving costs and differences in base amenities across locations.[43]

C.1.1 Solving for η_i^{kp} and T_i^k

First we solve for the regulatory shadow price of emissions using observed data under the 1997 nonattainment designations. 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 regulatory shadow price of emissions. Using our empirical estimates for β_η^p and the observed set of nonattainment designations, we can then recover the base regulatory shadow price of emissions:

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

This gives us the shadow price that firms face for emissions in the absence of nonattainment or first-best emissions pricing.

Next we solve for productivity. From equation (10) we have that:

$$Y_i^k = \kappa_2 \left[c_i^k\right]^{-\theta^k} T_i^k F M A_i^k \tag{19}$$

We can manipulate equation (19) and expand out the unit cost term c_i^k to obtain an expression

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

that gives us T_i^k up to a normalization:

$$T_i^k = \rho_1 \frac{L_i^k \left[w_i^k\right]^{\left((1+\theta^k\gamma\left(1-\sum_{q=1}^P \xi^{kq}\right)\right)} \prod_{q=1}^P (\eta_i^{kq})^{\xi^{kq}\theta^k}}{FMA_i^k}. \tag{20}$$

In equation (20) we still need to identify the firm market access variables FMA_i^k to obtain productivity T_i^k for $k = 1, \ldots, K$. We can do so by performing function iteration on the system of equations that implicitly define firm market access and consumer market access from Section 3:

$$FMA_i^k = \sum_{j=1}^N \frac{\left(\tau_{ji}^k\right)^{-\theta^k}}{CMA_j^k} X_j^k \tag{21}$$

$$CMA_i^k = \kappa_3 \sum_{j=1}^N \frac{\left(\tau_{ij}^k\right)^{-\theta^k}}{FMA_j^k} Y_j^k \tag{22}$$

where $Y_i^k = \frac{w_i^k L_i^k}{\gamma\left(1-\sum_{q=1}^P \xi^{kq}\right)}$, and $X_i^k = \alpha^k \sum_{l=1}^K w_i^l L_i^l$. Iterating on these equations yields both market access vectors up to a normalization. Next we insert the recovered FMA_i^k terms into equation (20) and use the observed 1997 data on labor, wages, and nonattainment status to recover T_i^k.

C.1.2 Simulating the Model Under Different Scenarios

Now that we have recovered the regulatory shadow price under the 1997 nonattainment designations η_i^{kp}, the base regulatory shadow price $\bar{\eta}_i^{kp}$, and productivity T_i^k, we can simulate the welfare effects of changing the regulatory shadow price of emissions through different nonattainment designations or first-best emissions pricing. Consider the case of computing the equilibrium outcomes under some set of counterfactual regulatory shadow prices of emissions $\eta_i^{kp\prime}$, which may be the base regulatory shadow prices in the case of no counties in nonattainment, the first-best emissions prices, or any other choice. Other primed variable indicate endogenous quantities under $\eta_i^{kp\prime}$.

0a. Solve for the 1997 price indices Use the observed labor and wages from 1997 in equations (21) and (22) to solve for consumer market access and thus the price indices for the observed 1997 nonattainment designations that generate the regulatory shadow prices of emissions η_i^{kp}.

0b. Initial guess Guess a vector of market wages and the labor distribution across markets under the counterfactual $\eta_i^{kp\prime}$.

1. Solve for the counterfactual price indices Use these guesses in equations (21) and (22) to solve for consumer market access and thus the price indices under the counterfactual nonattainment designations.

2. Solve for the change in amenities Compute the level of manufacturing emissions using the expression for relative expenditures on inputs for a Cobb-Douglas producer:

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

where nonmanufacturing emissions are always zero. Then, along with the 1997 wages, the counterfactual wage guess, and the price indices from steps 0a and 1, solve for the change in amenities in equation (2) from going from the 1997 designations to the counterfactual designations.

$$\frac{B_j^{l\prime}}{B_j^l} = \underbrace{\frac{\bar{B}_j}{\bar{B}_j}}_{=1} \left[\left(1 - \frac{\sum_{n=1}^{N} \sum_{p=1}^{P} md_{in}^p e_n^{p\prime}}{V_i^{k\prime}} \right) \Big/ \left(1 - \frac{\sum_{n=1}^{N} \sum_{p=1}^{P} md_{in}^p e_n^p}{V_i^k} \right) \right].$$

We assume that baseline, non-pollution component of amenities $\bar{B}_j$ does not change in response to nonattainment.[44]

3. Solve for the counterfactual mobility shares and labor distribution Manipulating equation (4), we can obtain the counterfactual mobility shares and labor distribution as a function of the wage and labor guesses; the observed wages, labor, and mobility shares under 1997 nonattainment; the computed 1997 and counterfactual price indices; and the computed change in amenities:

$$\pi_{ij}^{kl\prime} = \frac{\left[\frac{V_j^{l\prime} B_j^{l\prime}}{V_j^l B_j^l}\right]^{\iota} \pi_{ij}^{kl}}{\sum_{m=1}^{K} \sum_{n=1}^{N} \left[\frac{V_n^{m\prime} B_n^{m\prime}}{V_n^m B_n^m}\right]^{\iota} \pi_{in}^{km}} \tag{23}$$

$$L_i^{k\prime} = \sum_{m=1}^{K} \sum_{n=1}^{N} \pi_{ni}^{mk\prime} L_n^{m\prime} \tag{24}$$

[44] We are not able to recover the level of amenities, but we can recover the change in amenities given a change in the set of nonattainment statuses from the structure of equation (2).

where the V terms are real wages, $V_n^{0\prime} = V_n^0$ so that nonattainment does not change the payoff from nonemployment. The $L_n^{m\prime}$ terms on the right-hand side of equation (24) are the guesses while the left-hand side is the newly updated labor distribution guess.

4. Solve for wages We can then use the solved counterfactual labor distribution from step 3, counterfactual market access from step 1, counterfactual regulatory shadow prices of emissions, and the fundamental productivity in equation (20) to back out a new guess for the counterfactual level of wages.

5. Iterate on steps 1-4 until convergence We then repeat the process of solving for new distributions of labor, amenities changes, prices, and wages until the vector of real wages converges, where we define convergence to be that the sup norm of the relative change in real wages between two different iterations of step 4, is sufficiently small.

We run the solution algorithm with $\eta_i^{kp\prime} = \bar{\eta}_i^{kp}$ to recover our baseline of no counties in nonattainment. We run the solution algorithm with $\eta_i^{kp\prime}$ equal to the county-specific marginal damages of emissions in the case of first-best emissions pricing. For first-best emissions pricing we need to update the marginal damages in each iteration, reflecting that the distribution of workers changes as we iterate through the algorithm. Finally we compute the equilibrium outcomes under tighter nonattainment thresholds by setting $\eta_i^{kp\prime} = \bar{\eta}_i^{kp} \exp(\beta_\eta^p \tilde{N}_i^T)$ where $\tilde{N}_i^T$ is equal to 1 if the observed level of pollution in 1997 is above some counterfactual nonattainment threshold T and zero otherwise.

C.2 Welfare Derivation

With the model solutions in hand we can now compute the welfare consequences of changes in the regulatory shadow price of emissions. Let variables with primes be associated with a vector $\eta_i^{kp\prime}$, while unprimed variables be associated with η_i^{kp}. Recall that indirect utility from consumption and amenities is given by $V_i^k B_i^k$ and that mobility shares are governed by $\pi_{ij}^{kl} = \frac{(V_j^l B_j^l \bar{\delta}_{ij}^{kl})^\iota}{\sum_{m=0}^K \sum_{n=1}^N (V_n^m B_n^m \bar{\delta}_{in}^{km})^\iota}$. Rearrange and take the log of the expression for own-mobility shares to get:

$$\iota \log V_i^k B_i^k - \log \pi_{ii}^{kk} = \log \left[\sum_{m=0}^K \sum_{n=1}^N (V_n^m B_n^m \bar{\delta}_{in}^{km})^\iota \right]. \tag{25}$$

Let W_i be the expected total welfare for a household in location i net of moving costs:

$$W_i^k = \frac{1}{\iota} \log \left[\sum_{m=1}^K \sum_{n=1}^N (V_n^m B_n^m \bar{\delta}_{in}^{km})^\iota \right]$$

which is a function of unobserved moving costs. Next rearrange equation (25) and solve for W_i:

$$W_i^k = \log\left(V_i^k B_i^k\right) - \frac{1}{\iota}\log \mu_{ii}^{kk}.$$

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

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

Let $\widehat{x} \coloneqq x'/x$ for some variable x.

The consumption-equivalent welfare under $\eta_i^{kp\prime}$ relative to η_i^{kp} is χ_i:

$$\chi_i^k = \frac{\widehat{V}_i^k \widehat{B}_i^k}{\left(\widehat{\mu}_{ii}^{kk}\right)^{1/\iota}}.$$

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 effect of 1997 nonattainment relative to no counties in nonattainment, but under different calibrated parameter values and structural assumptions.

The first row reports the base welfare outcomes in the main text. Panel A shows the effect of changing parameter values. The first two rows vary the trade elasticity θ and show that the quantitative values are sensitive to it, but the qualitative takeaways remain the same. Why do the welfare impacts of 1997 nonattainment designations decline in θ? First, recall that the trade elasticity governs the dispersion in productivities within a location-sector: the larger this value is, the less variation there is in productivity across firms within a location-sector. Second, recall that consumer market access CMA_i, a measure of consumers' access to cheap suppliers, was proportional to $\sum_{n=1}^{N} T_n^k \left[c_n^k \tau_{in}^k\right]^{-\theta^k}$. The expression for consumer market access makes clear that under a larger trade elasticity, consumer market access becomes more sensitive to producer cost shocks driven by nonattainment designations, which is reflected in lower welfare.

The next four rows vary the consumption share parameter α and the labor share parameter γ. The quantitative results are insensitive to their values.

The next two rows vary the migration elasticity parameter ι. The smaller of the two values is similar to annual elasticities estimated for US workers in Artuc et al. (2010) and Caliendo et al. (2019).[45] This value for ι generates similar results to our baseline.

In general, a larger ι leads to smaller aggregate gains from 1997 nonattainment. The decline in welfare gains is slightly larger for nonattainment counties compared to attainment counties, and the decline is borne by nonmanufacturing. Nonmanufacturing welfare gains are smaller because if ι is larger, the idiosyncratic shock to the household ε is less dispersed, making it less likely they get a large positive draw to overcome moving costs that prohibit them from moving to nonattainment counties to take advantage of the improved amenities. Since nonmanufacturing is a majority of the working population, this leads aggregate welfare gains to be smaller with a larger migration elasticity.

The last three rows of the panel change the pollution elasticity parameters ξ^p by halving, doubling, or quadrupling them. Greater pollution elasticities tend to worsen the effect of

[45]These papers estimate the *inverse* migration elasticity and recover values of around 2.

nonattainment designations on manufacturing workers. Larger pollution elasticities mean that production is more emissions intensive and amplifies the importance of the costs of emissions for firms. Thus, nonattainment has greater negative effects, leading to larger decreases in nominal manufacturing wages and manufacturing welfare.

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 because of higher gains to nonmanufacturing.

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, relatively uniformly across sectors and county types.

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 productive 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 or decrease manufacturing welfare by 0.25pp because productivity shocks directly affect demand for manufacturing labor and manufacturing wages.

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)
	(1)	(2)	(3)	(4)	(5)	(6)
β_η^p	0.51**	0.50**	0.33**	0.50**	0.49**	0.48**
	(0.23)	(0.21)	(0.17)	(0.22)	(0.23)	(0.24)
Observations	19,005	28,940	38,890	49,245	59,610	70,225
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

Note: The coefficients are estimated using data from 1990, and from 1996 to the year listed in the Latest Year row. The 1991–1995 gap reflects years in which NEI data are not available. Robust standard errors are clustered at the state 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	0.57	0.18	0.63	0.36	0.78
A. Parameter Changes					
$\theta = 2$	1.22	0.88	1.26	0.75	1.68
$\theta = 8$	0.31	-0.19	0.38	0.19	0.42
$\alpha = 0.137$	0.57	0.18	0.63	0.36	0.78
$\alpha = 0.548$	0.57	0.18	0.63	0.36	0.78
$\gamma = 0.2405$	0.56	0.09	0.62	0.39	0.72
$\gamma = 1$	0.57	0.26	0.62	0.31	0.84
$\iota = 0.495$	0.63	0.12	0.7	0.36	0.89
$\iota = 2$	0.4	0.15	0.43	0.23	0.56
ξs Halved	0.6	0.35	0.63	0.36	0.83
ξs Doubled	0.52	-0.18	0.62	0.36	0.68
ξs Quadrupled	0.42	-0.9	0.59	0.35	0.48
B. Structural Changes					
Add Congestion/Agglomeration	0.62	0.04	0.71	0.37	0.87
VSL Increases in Income	0.42	0.08	0.47	0.24	0.59
Increase Productivity 3 Percent	0.61	0.43	0.64	0.36	0.85
Decrease Productivity 3 Percent	0.53	-0.08	0.62	0.35	0.71

Note:
Welfare is computed as the equivalent 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.

E Supporting Results

Exogenous Nonattainment and the Length of Nonattainment Designations Figure E1 plots the share of counties that remaining in nonattainment over a 10 year period from 1992–2001 amongst the set of counties that were induced to go into nonattainment under the 1990 amendments. In the first full year, 1992, all of the counties are in nonattainment. Five years later, only one-third of counties exited nonattainment, and ten years later less than half of these counties exited nonattainment. This indicates that nonattainment designations are generally long-lasting and supports our assumption that nonattainment designations persist into a new equilibrium.

Congestion and Agglomeration Figure E2 plots the change in welfare gains if the model accounts for congestion and agglomeration effects. Similar to reallocation, congestion and agglomeration have highly heterogeneous welfare effects. Congestion effects tend to dominate agglomeration effects given our parameterization from Allen and Arkolakis (2014). Thus, incumbents in places where people are migrating to tend to be worse off with congestion and agglomeration while incumbents in places they are leaving tend to be better off.

Productivity Effects Figure E3 plots the change in 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 has welfare impacts in nonattainment counties about one-tenth the size of the productivity effect, but does not meaningfully change the geography of the results as the magnitudes of the effects are relatively small.

First-Best Versus Actual 1997 Nonattainment Welfare 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 and all counties are better off.

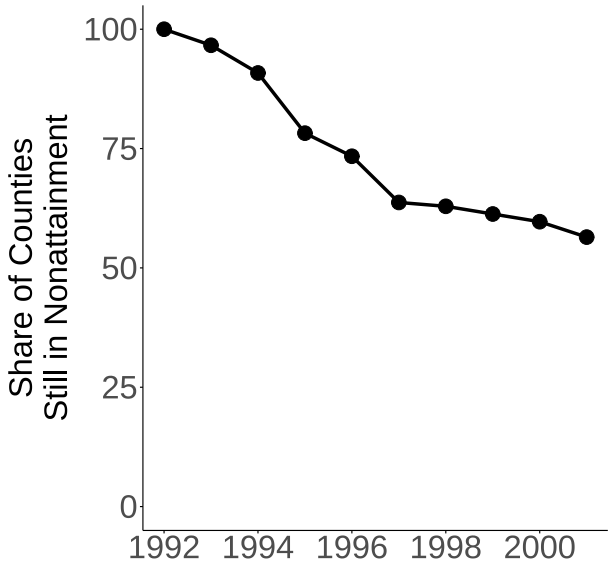
First-Best Emission Prices Figure E5 plots the emission prices under the first-best emission pricing policy. Recall that these prices are on top of the base regulatory shadow price of emissions from other prevailing regulations besides CAA nonattainment. Prices are highly heterogeneous across space and pollutants. Prices tend to be highest around urban areas and for $PM_{2.5}$ and SO_2. Notice that first-best prices are near-zero in some nonattainment counties and are substantially positive in some attainment counties. The

figure also shows why counties in the east benefit the most from first-best pricing: the price that firms face for emissions is too low.

Across all pollutants, the regulatory shadow price of emissions is too high in nonattainment counties and too low in attainment counties. For example, for $PM_{2.5}$, the average difference between the regulatory shadow price and the first-best price in nonattainment counties is nearly \$250,000/ton, while in attainment counties it is -\$800/ton. These kinds of mismatches between first-best prices and the regulatory shadow price of nonattainment are why first-best pricing leads to significant welfare gains, it corrects a mispricing of emissions under the NAAQS.

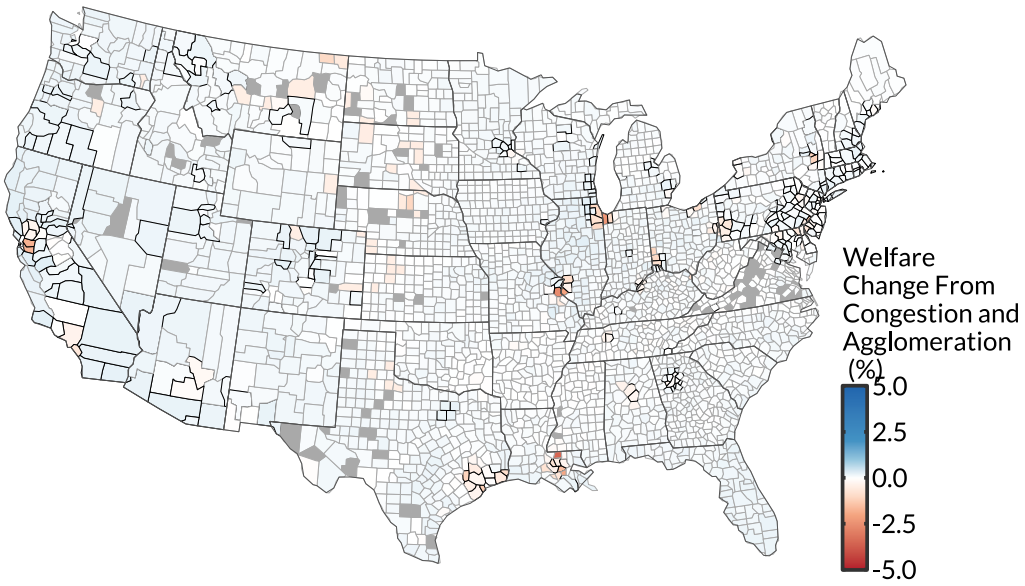
Reallocation Under First-Best Figure E6 shows the welfare gain from endogenous labor reallocation under the first-best pricing scheme. Notice that this looks substantially different than the gains under nonattainment shown in Figure 6. Under 1997 nonattainment, the value of labor reallocation is highest in nonattainment counties and the counties nearby as manufacturing workers can switch jobs or move to avoid the real wage penalty of nonattainment, and nonmanufacturing workers can move into nonattainment counties to reap the improved amenities. Under the first-best, reallocation is most valuable in the Southeast where emissions are underpriced by the prevailing nonattainment designations, while reallocation actually has negative consequences in the West. This is because workers in the Southeast move westward in response to first-best pricing, depressing incumbents' real wages in the West. In terms of sectoral reallocation, the aggregate changes in the share of workers across manufacturing, nonmanufacturing, and nonemployment are largely similar between the 1997 nonattainment outcomes and the first-best. The first-best results in a slightly smaller share of workers transitioning out of manufacturing, however the difference between the two is only 0.07pp, under one-tenth of the transition caused by 1997 nonattainment.

Figure E1: The share of new nonattainment counties remaining in nonattainment by year 1992–2001.



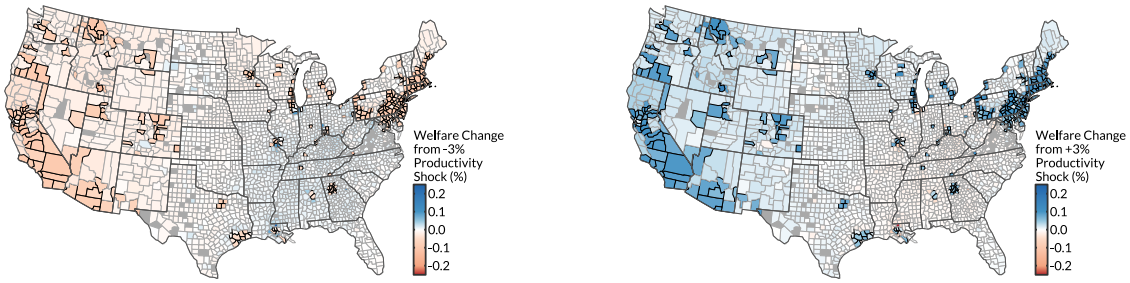
Note: Each point denotes the share of counties, amongst the set that newly went into nonattainment after the 1990 amendments, that remain in nonattainment each year.

Figure E2: The change in welfare gains from 1997 nonattainment from congestion and agglomeration.



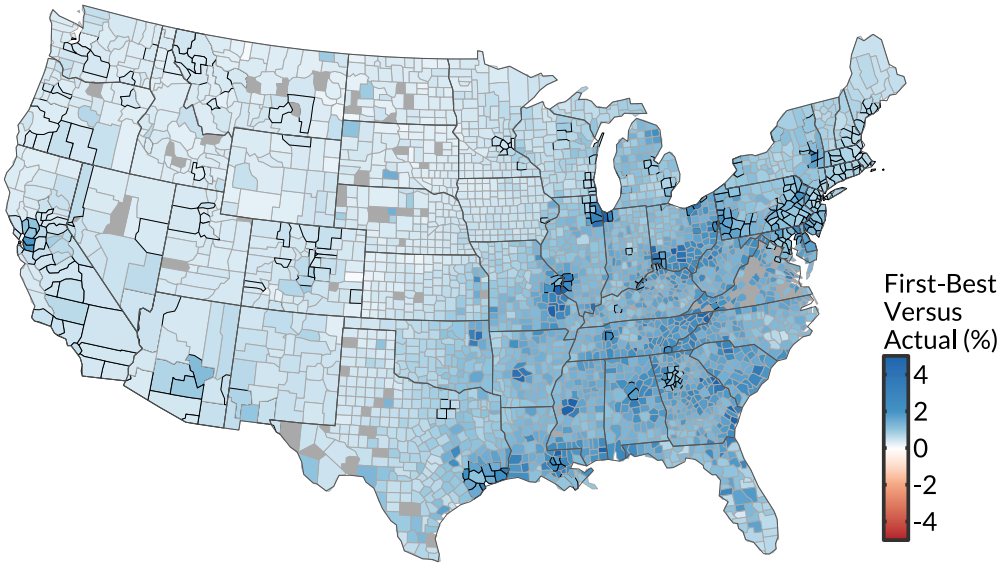
The change in welfare is the difference between the welfare calculated by the model using the 1997 nonattainment status provisions relative to the welfare calculated under a counterfactual scenario in which no counties are in nonattainment, with congestion and agglomeration effects versus without. Welfare is calculated as equivalent variation; it is reported in consumption-equivalent terms. 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 E3: The change in welfare gains from 1997 nonattainment from if there are ±3 percent effects on total factor productivity in manufacturing.



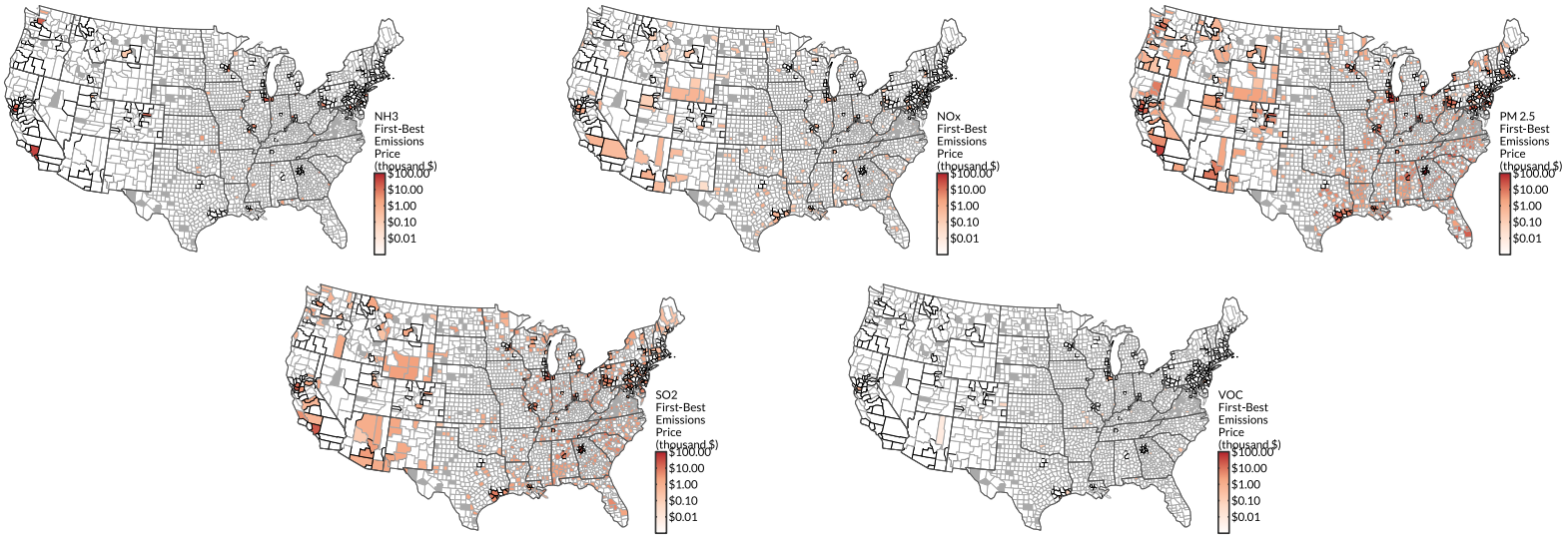
Note: The left panel decreases manufacturing productivity by 3 percent on top of the emissions price effects. The right panel increases manufacturing productivity by 3 percent on top of the emissions price effects. The change in welfare is the difference between the welfare calculated by the model using the 1997 nonattainment status provisions relative to the welfare calculated under a counterfactual scenario in which no counties are in nonattainment, with the productivity effect versus without. Welfare is calculated as equivalent variation; it is reported in consumption-equivalent terms. 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 calculated as equivalent variation; it is reported in consumption-equivalent terms. 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.

Figure E5: First-best counterfactual emission prices.



Note: Each panel plots the pollutant-specific first-best emission price as the spatially differentiated tax equal to the marginal damages caused by a unit of emissions in a county, above the base regulatory shadow price of emissions which captures other regulations besides CAA-induced nonattainment. The tax accounts for how workers may have migrated or changed industries in response to the tax. 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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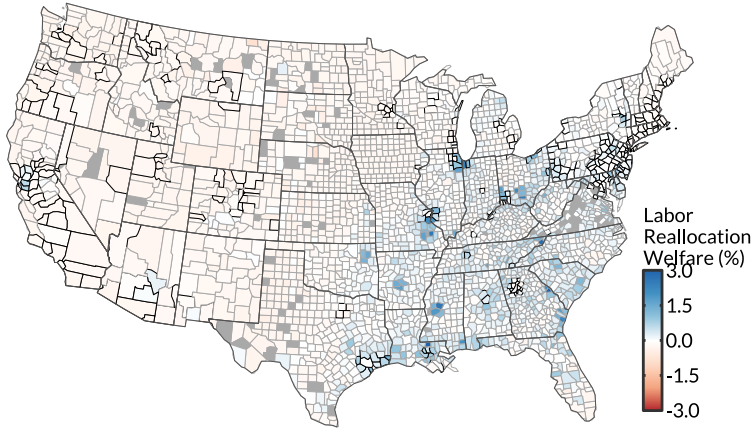
Figure E6: The change in welfare from endogenous labor reallocation under first-best emissions pricing.



Note: The top right panel shows the change in total welfare from labor reallocation through migration and changing sector of employment under first-best emission pricing. The change in welfare is the difference between the welfare calculated by the model using the first-best prices with labor reallocation versus without labor reallocation. Welfare is calculated as equivalent variation; it is reported in consumption-equivalent terms. 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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