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ECONOMIC GEOGRAPHY AND THE EFFICIENCY OF ENVIRONMENTAL REGULATION

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ABSTRACT

We develop a spatial equilibrium model to evaluate the efficiency and distributional impacts of the leading air quality regulation in the United States: the National Ambient Air Quality Standards (NAAQS). We link our economic model to an integrated assessment model for air pollutants which allows us to capture endogenous changes in emissions, amenities, labor, and production. Our results show that the NAAQS generate over $23 billion of annual welfare gains. This is roughly 80 percent of welfare gains of the second-best NAAQS design, but only 25 percent of the first-best emission pricing policy. The NAAQS benefits are concentrated in a small set of cities, impose substantial costs on manufacturing workers, improve amenities in counties in compliance with the NAAQS, and reduce emissions in compliance counties through general equilibrium channels. These findings highlight the importance of accounting for geographic reallocation and equilibrium responses when quantifying the effects of environmental regulation.

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1 Introduction

Over the last several decades, governments have enacted numerous regulations intended to improve environmental quality. Environmental protections directly benefit individuals through improved health, recreation, and other channels, but more stringent regulation of polluting activities imposes substantial costs on producers. Historically, environmental regulations have often been standards, mandating that firms adopt specific types of technologies, or requiring pollution to be below certain levels.[1] In general, these policies are neither cost-effective nor efficient: they do not equalize the marginal costs of abatement across sources nor do they equalize the marginal costs of abatement with the marginal damages of emissions. Understanding whether these policies approach the welfare gains of second- or first-best policies is challenging. Such an analysis requires information on abatement costs and damages in combination with a quantitative model capturing equilibrium responses and heterogeneity across space and sectors.

In this paper we evaluate the efficiency and distributional effects of the primary air quality regulation in the United States: the National Ambient Air Quality Standards (NAAQS) under the Clean Air Act (CAA). The NAAQS are a set of standards on ambient concentrations of six criteria pollutants. If air pollution concentrations within a county exceed these standards, the county is out of compliance and designated as in *nonattainment*. Polluting plants in nonattainment counties are mandated to adopt costly abatement technologies in addition to other burdensome requirements. We evaluate the NAAQS by building a multi-sector economic geography model where emissions are caused by production of output, goods are traded across locations, and labor is imperfectly mobile across space and sectors. We apply the model to US counties and allow local productivity and emissions to be a function of the NAAQS, capturing how environmental regulations incentivize emissions reductions and raise firm costs.

A novel feature of our paper is that we link the underlying economic geography model to a benchmark integrated assessment model for air pollution.[2] This allows us to map the regulation-induced changes in emissions into changes in ambient pollution and local amenities across all US counties (Muller and Mendelsohn, 2009; Tschofen, Azevedo and

[1] For example, the New Source Performance Standards under the 1970 Clean Air Act and 1977 Clean Air Act Amendments effectively mandated new coal plants to adopt SO_2 scrubbers, and mandated new model-year cars to have catalytic converters. The Clean Water Act required wastewater treatment facilities to upgrade to secondary treatment technologies, and required tertiary treatment technologies for point sources when a water body does not meet total maximum daily load requirements.

[2] This is similar in spirit to Holland, Mansur, Muller and Yates (2016) and Holland, Mansur, Muller and Yates (2019) who combine econometric models with an air quality integrated assessment model to estimate impacts of electric vehicle adoption and second-best policy design. We use a quantitative spatial equilibrium model which represents the entire economy and allows for fully endogenous pollution responses.

Muller, 2019; Clay, Jha, Muller and Walsh, 2019), while also accounting for responses to environmental regulation that drive further endogenous changes in emissions and amenities.[3] Air pollutants are spatially local, with higher concentrations near the source of emission and lower further away. This "physical geography" along with economic frictions mean that the benefits and costs of environmental policy will be distributed heterogeneously across space, sectors, and households. Our approach allows us to account for these factors and how the economy responds to changes in regulation, which is critical for quantifying the efficiency and distributional implications of environmental policy.

We produce two main sets of results. First, the 1997 NAAQS pollution concentration thresholds for nonattainment designations were not optimal, but achieved 80 percent of the welfare improvements of the second-best NAAQS standards. Despite being close to second-best, the 1997 NAAQS only achieved 25 percent of the welfare gains from using the first-best emission pricing policy. Virtually the entire population is worse off under the NAAQS relative to first-best, indicating they are nearly Pareto-dominated. Second, the set of nonattainment designations in 1997 delivered \$23 billion in benefits per year. Approximately one-fifth of these benefits actually accrued to workers in counties that were in compliance with the NAAQS, and the benefits of regulation were highly concentrated around a few major cities.

To take our model to the data and simulate counterfactuals, we first estimate how the NAAQS affect firm productivity and emissions. We estimate the parameters using the spatial equilibrium conditions of the model to ensure that our estimates account for the role of general equilibrium spillovers across treatment versus control units and therefore avoid violations of the Stable Unit Treatment Value Assumption (SUTVA).[4,5]

To estimate the direct effects on emissions and productivity in spatial equilibrium, we exploit quasi-experimental variation in county-level nonattainment status due to changes in the NAAQS under the 1990 CAA amendments. The 1990 CAA amendments increased regulatory scrutiny and costs to polluting firms by introducing a new class of pollutants to

[3]We abstract away from an explicit representation of the effect of emissions on labor productivity (e.g Chang et al., 2016, 2019; He et al., 2019). We focus on estimating the effect of the NAAQS on productivity, which partially captures how regulation-induced pollution reductions increase productivity.

[4]The macroeconomics literature has recently grappled with SUTVA issues in identifying the regional impacts of shocks that may spillover and propagate throughout the economy (e.g. Mian and Sufi, 2014; Nakamura and Steinsson, 2014; Chodorow-Reich, 2020). Adao, Arkolakis and Esposito (2020) develop a sufficient statistics methodology to recover the size of the spatial general equilibrium effects.

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

the NAAQS — particulate matter smaller than 10 micrometers in diameter (PM_{10}) — and scheduling a formal re-evaluation of the current set of nonattainment designations. This led to the largest change in nonattainment since 1978 (Walker, 2013). Reduced form evidence has shown that nonattainment designation makes it more costly for polluting firms to enter, induces exit of incumbent firms, and has negative effects on the polluting industry's workforce, output, and productivity (Henderson, 1996; Becker and Henderson, 2000; Greenstone, 2002; Walker, 2013).

We estimate the impact of nonattainment designations on the implicit marginal cost (i.e. shadow price) that firms face for emissions by comparing emissions before and after the new nonattainment designations, in nonattainment versus attainment counties, while conditioning on the wage bill.[6] We find the implicit marginal cost of emitting five particulate matter precursors increases by an average of 35 percent, but with significant heterogeneity.

We estimate the effect of nonattainment status on productivity using a triple difference approach where we compare polluting to nonpolluting industries. We find that nonattainment designations decrease productivity of polluting sectors by 3.5 percent. One feature of this result is that it highlights the importance of accounting for general equilibrium spillovers for the purposes of policy evaluation. Directly controlling for wages and market access allows us to isolate the direct impact of nonattainment status on productivity because these variables are sufficient statistics for spatial and sectoral linkages. This source of bias is important in our context and would lead to underestimating productivity effects by one-fourth. This suggests that accounting for general equilibrium spillovers may be an important in other empirical settings.

With these estimates in hand, we then quantify aggregate and distributional impacts using our model. In particular, we conduct counterfactuals that simulate 1997 equilibrium outcomes as if counties never went into nonattainment.[7] Using the exact hat algebra approach in Dekle, Eaton and Kortum (2008) we compute changes in welfare, sectoral employment, and population outcomes under the actual nonattainment designations with a counterfactual scenario in which no county is in nonattainment. The results imply a 0.53 percent increase in welfare from improved amenities through lower fine particulate concentrations, and a 0.14 percent decrease from lower real wages driven by lower productivity. Overall, welfare increases by 0.39 percent or \$23 billion per year. In present value terms at a three percent discount rate, total benefits are over \$700 billion.[8] We then show that the

[6] Controlling for the wage bill is theoretically important for separately identifying the direct effect of nonattainment on the implicit marginal cost of emissions from equilibrium changes in the scale of the industry. In practice, this adjustment does not affect the estimated coefficients.

[7] 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.

[8] The actual net benefits are likely even larger. Our quantitative model only accounts for damages from

1997 set of NAAQS standards ambient pollution thresholds are not second-best, achieving 80 percent of the welfare gain of applying the optimal, second-best NAAQS thresholds, but only 25 percent of the first-best emission price. Taken together, our results suggest that further refinements of the NAAQS provide little benefit compared to a wholesale change to a fully market-based regulatory approach.[9]

To understand the forces underlying these results we next decompose the effects across sectors and regions. In the aggregate, workers in polluting sector are worse off while workers in the nonpolluting sector are better off. The polluting sector in our setting (manufacturing), has workers experiencing real wage losses of 0.76 percent, about double their welfare gains from improved amenities. Workers in nonpolluting sectors (nonmanufacturing) experience larger welfare gains since the impact on their real wages is only -0.07 percent. The per capita welfare gains are also highly unequal across space and accrue mostly to several high population, urban counties and other counties nearby.

Finally, we quantify the economic and physical mechanisms that shape the margins of adjustment. In response to effects of nonattainment on productivity and the price of emissions, labor reallocates across space and industries. Reallocation has a positive effect on real wages as suggested by standard economic theory and previous work (Andersen, 2018), but in our setting it also has a positive effect due to reallocating emissions to areas that are lower marginal damage in the new equilibrium. Changes in productivity and the implicit marginal cost of emissions also lead to changes in emissions and amenities in all counties. Our quantitative results show that about 10 percent of the amenities gains occur in attainment counties and about half of the improvements in amenities are from avoiding pollution that crosses county borders into other attainment and nonattainment counties. The results also show that the NAAQS induced negative leakage — a phenomenon hypothesized by the theoretical literature (Baylis et al., 2014) — and reduced emissions in attainment counties through general equilibrium channels. These findings highlight the role of accounting for physical and economic processes when evaluating the benefits of environmental policy.

Our paper contributes to several strands of the literature on environmental regulation. The first is focused on evaluating the efficiency of environmental regulation. This literature has found that market-based regulation can lead to significant welfare gains from improving cost-effectiveness (Carlson, Burtraw, Cropper and Palmer, 2000; Fowlie, Knittel and Wolfram, 2012; Lade and Rudik, 2020). Despite these cost reductions, flexibility to reallocate local pollutants across space has worsened welfare under other CAA regulations by moving

formation of $PM_{2.5}$, and our reduced form amenity regression in the appendix suggests that the amenity benefits may be over three times larger.

[9] One market-based aspect of the NAAQS is that new entrants must purchase pollution offsets from existing firms so that total emissions in a county do not increase (Shapiro and Walker, 2020).

emissions into higher damage areas (Henry, Muller and Mendelsohn, 2011; Chan, Chupp, Cropper and Muller, 2018).

This paper is also related to a large empirical literature on the impact of environmental regulation and, more specifically, the Clean Air Act. One strand of this literature estimates the effect of the NAAQS and nonattainment designations. The NAAQS have well-documented air quality and health benefits (Chay et al., 2003; Auffhammer et al., 2009; Isen et al., 2017), and these benefits are capitalized into housing values and rents (Chay and Greenstone, 2005; Grainger, 2012; Bento et al., 2015). However, these benefits come at a cost. Several papers have found negative effects on firms through reduced productivity and reduced competitiveness, and negative effects on workers through lower wages, and increased rates of nonemployment and costly job transitions (Becker and Henderson, 2000; Greenstone, 2002; Greenstone et al., 2012; Walker, 2013).[10]

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

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

Our paper sheds new light on the impacts of the Clean Air Act. We show that in annualized terms, billions of dollars of benefits from improved amenities, and that hundreds

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

of millions of dollars of benefits from improved real wages, actually accrue to counties that never enter nonattainment. The amenity benefits are driven by cross-county spillovers of pollution reductions while the income benefits are driven mostly by the reallocation of labor and decreased competition facing firms in attainment counties.

These physical and economic spillovers reveal several important facts. First, and most importantly, the welfare benefits of the NAAQS are larger than previously estimated. Second, the empirical literature estimating the value of improved air quality by comparing nonattainment and attainment counties has been biased due to violations of the Stable Unit Treatment Value Assumption through economic and physical channels. Attainment counties account for about one-fifth of the total welfare gains which suggests the magnitudes of the bias may be substantial. Third, labor market reallocation has highly heterogeneous effects. Reallocation reduces welfare in some major population centers by up to 3 percent — eight times the average welfare gain from nonattainment — because of pecuniary and real externalities. The largest gains from reallocation are only 0.4 percent.

Finally, our paper is related to a recent line of research using economic geography models to examine the economic impacts of environmental change (Dingel, Meng and Hsiang, 2018; Aldeco, Barrage and Turner, 2019; Hanlon, 2020; Balboni, 2021; Heblich, Trew and Zylberberg, 2021; Cruz and Rossi-Hansberg, 2021; Nath, 2021; Rudik, Lyn, Tan and Ortiz-Bobea, 2021).[11] We add to this literature by studying environmental regulation and its impact on the environment by integrating standard features of economic geography models with a workhorse air pollution integrated assessment model. Our paper highlights the contribution of environmental quality to urban amenities and its role in the recent revitalization of American cities (Kahn and Walsh, 2015; Baum-Snow and Hartley, 2020; Couture and Handbury, 2020).

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

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

2 Institutional Setting

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

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

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

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

3 Model

We develop a Ricardian model of interregional trade for the United States in the spirit of Eaton and Kortum (2002).[12] In the model, there are N counties indexed by i, j, n, and K industries indexed by k, l, m. Firms use labor and capital as inputs into production. Production generates emissions — or isomorphically, emissions are an input to production (Copeland and Taylor, 2013). Emissions are not traded in markets, but firms face an implicit marginal cost of emissions imposed by the prevailing set of local environmental regulations. Labor is supplied inelastically and is imperfectly mobile across locations and industries; capital is perfectly mobile so that the rental rate is equalized across locations.

Differences in productivity and implicit emissions prices across counties and industries determine the allocation of labor and emissions, and hence the spatial and sectoral distribution of economic activity. In our model, we incorporate nonattainment designations that affect both the implicit marginal cost of emissions and factor productivity in the polluting sector. We take nonattainment designations to be exogenous so that potential reallocation of emissions across space does not endogenously induce a county to be in nonattainment.[13]

3.1 The Household Problem

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

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

[12]We abstract away from offshoring dirty production outside the US. Recent work indicates that this is not a major factor in changes in US manufacturing emissions (Shapiro and Walker, 2018).

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

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

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

where P_i^k is the CES price index of goods purchased from industry k for final consumption in county i that we will define below. A consumer's indirect consumption utility V_i^k is their real wage if employed, and is equal to home production b_i if nonemployed:

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

Location-specific amenities B_i are determined by a host of local factors including ambient pollution concentrations.[14] Local ambient pollution a_i is a function of emissions in all locations: $a_i = A_i(\boldsymbol{e})$ where $\boldsymbol{e} = (e_1^1, \dots, e_N^1, \dots, e_1^2, e_N^2, \dots, e_1^P, \dots, e_N^P)$ is a vector of emissions e_i^p of pollutant p in location i where there are P different kinds of emitted pollutants and $p = 1, \dots, P$.[15] This setup reflects two features that are relevant in our empirical setting. First, different emitted pollutants may contribute to the ultimate formation of ambient pollution a_i. For example, ammonia, nitrogen oxides, sulfur dioxide, and volatile organic compounds are precursors to ambient particulate matter. Second, emissions can move across counties, and therefore affect ambient concentrations and amenities in other locations, imposing cross-county externalities.

We specify A_i as the atmospheric transportation model in AP3 (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

[14] An alternative approach is to specify a reduced form relationship between local amenities B_i and nonattainment status. This provides a separate theoretical representation of amenities and implies a different empirical approach to quantifying the the effect of nonattainment on amenities. Our preferred approach is to incorporate emissions directly. That said, in Appendix A, we discuss the alternative reduced form method as well as the associated empirical results. In general, this approach provides an upper bound on the size of the amenities improvements and also validates using a model where labor migrates in response to nonattainment-induced amenity improvements.

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

the economic damages from emissions of air pollutants. The atmospheric transportation model simulates how one ton of pollutant p emitted in any county i translates into changes in ambient concentrations of fine particulate matter ($PM_{2.5}$) in all counties in the United States.[16] 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 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.[17] The right panel of Figure 1 shows how per capita damages change if the one thousand metric tons of nitrogen oxides were emitted in Los Angeles instead of St. Louis. Gains and losses are concentrated near the two counties of interest, however there are non-negligible welfare impacts across the entire United States.

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

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

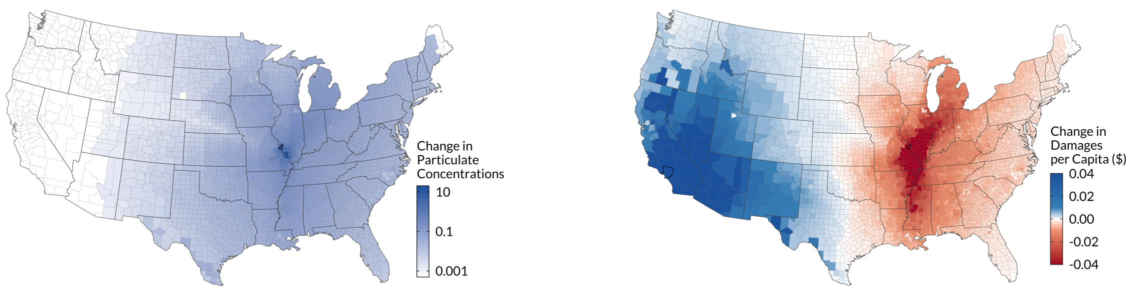
where $\bar{B}_i$ is the baseline level of amenities and the second term captures the reduction in amenities. Since we do not observe home production $b_i = C_i^0$, we assign C_i^0 to be the population-weighted average real wage in location i for the purpose of computing changes in amenities within the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

Labor is mobile across counties, but moving from (j, m) to (i, k) incurs a utility cost $\delta_{ji}^{mk} \in (0, 1]$ where $\delta_{jj}^{kk} = 1$ for all $j = 1, \ldots, N$ and $k = 0, \ldots, K$. Moving costs have a

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

[17] Muller and Mendelsohn (2007) provides a detailed description.

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



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

deterministic component $\bar{\delta}_{jn}^{ml}$ and an idiosyncratic random component ε:

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

where ε is drawn from a Fréchet distribution. This implies the share of households that migrate from (j, m) to (i, k) is:

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

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

3.2 The Firm Problem

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

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

This model is isomorphic to one where the firm operates a Cobb-Douglas production technology with labor and capital as inputs, emissions are produced as a byproduct, and firms have an abatement technology (Copeland and Taylor, 2013). One unit of output generates one unit of emissions subject to the appropriate normalization of units.[18] ω denotes different varieties, p indexes different pollutants $p = 1, \ldots, P$, $\gamma \in [0, 1]$ is the labor share, and capital is perfectly mobile across space and sectors. $z_i^k(\omega)$ is variety-specific productivity. To simplify the exposition, from hereon we omit varieties from the notation whenever the mathematics remain clear.

3.2.1 Emissions

The equilibrium emissions intensity of output for pollutant p is given by:

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

where P_i^k is the industry price index which we define below and η_i^{kp} is the exogenously given implicit marginal cost or price of emissions faced by the firm for pollutant p. 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.

[18] $e_i^{kp}/q_i^k = 1$ 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.

3.2.2 Productivity

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

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

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

The fundamental productivity of county i has two parts:

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

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

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

3.2.3 Prices and Market Clearing

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

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

where Ω is a constant, r_i^k is the capital rental rate and the assumption of perfect capital mobility implies that $r_i^k = r$ for all i, k.

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

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

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

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

where κ is a constant. A transformation of the price index, $(P_i^k)^{-\theta^k}$, is called consumer market access (CMA_i^k) and captures county i's access to cheaper products. An analogous term for the firm side is firm market access:

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

which captures firms' access to larger markets and where Y_j^k is output in market (k, j). These terms are equivalent up to a normalization and so we define market access MA_i^k as:[19]

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

where ρ is a constant.

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

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

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

We denote trade shares as:

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

and total expenditures as:

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

Finally, labor market clearing requires:

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

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

4 Data

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

4.1 Nonattainment Status

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

4.2 Emissions

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

4.3 Economic Activity by Sector

We draw on data from the Bureau of Economic Analysis to capture county-level economic activity by industry. Specifically, we use information on payroll and employment by industry each year from 1986 to 2001. We aggregate the industry-level data to groups that encompass polluting and nonpolluting sectors. For the polluting sector, we focus on employment in manufacturing. For the nonpolluting sector, we include employment in industries not in manufacturing and also exclude utilities. Fossil fuel plants emit a wide range of criteria pollutant precursors, but are the primary industry covered by the Acid Rain Program — another new regulation under the 1990 CAA amendments that is not the focus of our analysis.

4.4 Geographic and Sectoral Mobility

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

4.5 Bilateral Trade Costs and Market Access

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

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

We then combine trade cost and employment data to construct market access for each year by solving the system of equations given by: $MA_i^k = \rho_2 \sum_{j=1}^{N} \tau_{ji}^{-\theta^k} \left(MA_j^k\right)^{-1} w_j^k L_j^k$, where τ_{ji} is the matrix for trade costs and $w_j^k L_j^k$ is the sector-specific wage bill.[20] This requires calibrating the trade elasticity θ^k, which we set to 4 as described below. We also consider robustness to alternative values.

5 Estimating the Effects of Nonattainment Status

The spatial equilibrium model in Section 3 allows us to estimate the impact of nonattainment in an internally consistent way. In this section, we derive our estimating equations to illustrate how general equilibrium channels have potentially important consequences for estimating the parameters of interest, i.e., β_η^p and β_T^k.

5.1 Emissions

We first estimate the effect of nonattainment status on the local implicit marginal cost of emissions. We use equation (2) together with the expression for labor's share of firm revenues to obtain an expression for emissions as a function of nonattainment status, the endogenous industry wage bill, emissions elasticities, and the unobserved base emissions price:

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

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

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

Our estimating equation is:

$$\log\left(e^p_{i,t}\right) = -\beta^p_\eta N_{i,t} + \log\left(w_{i,t}L_{i,t}\right) + \psi_i + \nu_{p,t} + \varepsilon^p_{i,t} \tag{12}$$

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

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

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

Table 1 reports our estimates based on equation (12). Panel A reports the average effect of any nonattainment designation across all criteria pollutant types. 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 3 and 4 include the wage bill control and fix its coefficient to its model-implied value. The results across all four columns are highly consistent and indicate that nonattainment raises the implicit marginal cost or marginal cost of emissions by 42–45 percent. Note that since the estimates are large, the percentage effect is given by $\exp(\beta) - 1$ and the small value approximation of β^p_η is not valid.

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

5.2 Productivity

We estimate the effect of nonattainment status on local productivity in two steps. We first estimate a composite effect of nonattainment and both productivity and the implicit emissions price, then we use our emissions estimates above to isolate the effect on productivity. We start by combining equations (6), (7), (8), and (11) to obtain an condition for equilibrium industry income:

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

Following Walker (2013), we estimate triple difference specifications that exploit variation in nonattainment status at the county level over time as well as variation across polluting versus nonpolluting industries within each county. Similar to our approach for emissions, we use the quasi-experimental variation from counties newly assigned to nonattainment under the 1990 CAA amendments. The identifying variation for the effect of nonattainment on productivity comes from comparing polluting sectors subject to nonattainment enforcement to nonpolluting sectors in attainment versus nonattainment counties, before and after a county enters nonattainment.[21]

Substituting in the expression for the input cost bundle in equation (5), taking the logarithm of both sides, and rearranging gives the log of industry income as a function of nonattainment status, an adjustment for endogenous and observable industry wages, endogenous market access, emissions elasticities, and the unobservable base productivity and

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

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

	(1)	(2)	(3)	(4)
A. Combined				
β_η^p	0.35**	0.35**	0.37**	0.37**
	(0.15)	(0.15)	(0.15)	(0.15)
B. By Emitted Pollutant				
Ammonia ($\beta_\eta^{NH_3}$)	2.0***	1.9***	2.0***	1.9***
	(0.39)	(0.39)	(0.39)	(0.39)
Nitrogen Oxides ($\beta_\eta^{NO_x}$)	0.47**	0.50***	0.49***	0.52***
	(0.19)	(0.19)	(0.19)	(0.19)
Fine Particulates ($\beta_\eta^{PM_{2.5}}$)	0.17	0.18	0.19	0.21
	(0.26)	(0.27)	(0.28)	(0.28)
Sulfur Dioxide ($\beta_\eta^{SO_2}$)	0.24	0.23	0.26	0.25
	(0.21)	(0.21)	(0.21)	(0.21)
Volatile Organics (β_η^{VOC})	0.42**	0.40*	0.44**	0.42**
	(0.20)	(0.20)	(0.20)	(0.20)
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
Wage Bill	Omitted	Omitted	Coef. Fixed	Coef. Fixed

Notes: The table shows estimates for versions of equation (12). Each coefficient can be interpreted as a semi-elasticity, the percent change in emissions. Panel A reports estimates of the coefficient on nonattainment status. Panel B reports estimates of the coefficient on nonattainment status interacted with a dummy variable for each pollutant. Columns 1 and 3 only include county, year, and pollutant fixed effects; Columns 2 and 4 replace the year and pollutant fixed effects with pollutant-year fixed effects; Columns 3 and 4 include the wage bill control and fix the coefficient at its theoretically-consistent value of 1. Robust standard errors clustered at the county level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

emissions price (i.e., the components not due to nonattainment):

$$\log\left(Y_i^k\right) = \underbrace{\left(\beta_T - \theta^k \sum_{p=1}^{P} \xi^{kp}\beta_\eta^p\right) N_i}_{\text{nonattainment}} + \underbrace{\log\left(\tilde{w}_i^k\right)}_{\text{wage adjustment}} + \underbrace{\log\left(MA_i\right)}_{\substack{\text{market access}\\ \text{adjustment}}}$$
$$- \underbrace{\theta^k(1-\gamma)\left(1 - \sum_{q=1}^{P} \xi^{kq}\right)\log\left(r\right)}_{\text{common rental rate}} + \underbrace{\log\left(\bar{T}_i^k\right) - \theta^k \alpha \log\left(\bar{\eta}_i^k\right)}_{\substack{\text{base productivity}\\ \text{and emissions price}}}$$

where $\tilde{w}_i^k = w_i^{k^{-\theta^k\gamma\left(1-\sum_{q=1}^{P}\xi^{kq}\right)}}$. The wage and market access adjustments are theoretically important for two reasons. First, income, wages, and market access are all determined in equilibrium and we need to condition on the latter two in order to isolate the direct effect of nonattainment on productivity.[22] Industry income will change because of changes in prices, but we want to isolate the effect on productivity using variation in observable income. Second, nonattainment designations tend to be positively spatially correlated as shown in Figure 2. A market's wages and market access — and thus industry income — will be affected by nearby markets' nonattainment designations because they will raise input prices and decrease productivity of competing firms. Nearby markets' nonattainment is thus an omitted variable and correlated with own nonattainment, introducing omitted variable bias.

The estimating equation is given by:

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

The estimated coefficient on nonattainment status, $\left(\beta_T - \theta^k \sum_{p=1}^{P} \xi^{kp}\beta_\eta^p\right)$, reflects a composite effect on productivity and the implicit emissions price. Using our estimates of β_η^p above, we can isolate β_T. $\exp(\beta_T) - 1$ gives us the reduction (in percent) in the scale parameter of the Fréchet distribution, which governs county-industry productivity.

The theory suggests that the coefficients on the wage and market access terms are 1. In practice, we consider alternative approaches that omit wages and market access from the estimating equation or set the coefficient equal to the value consistent with the theory. Our preferred approach to fix the coefficients at 1. We also fix the value of θ^k at 4, which is drawn from Simonovska and Waugh (2014), and we fix the ξ^{kp} elasticities at the median

[22] Rental rates are also determined in equilibrium but since capital is perfectly mobile rental rate adjustments will be absorbed by year fixed effects.

industry-specific values estimated by Shapiro and Walker (2018). We fix the value for NH_3 to their estimate for $PM_{2.5}$ since no direct estimate for NH_3 is available and $PM_{2.5}$ is the broadest category of pollution. We assume that the nonpolluting sector has no emissions and therefore that these emission elasticities are zero. The values of these elasticities are reported in Table B1 in the appendix. Table D3 in the appendix shows that our estimates are robust to other choices of trade and pollution elasticities.

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

Table 2 reports our estimate of $\left(\beta_T - \theta^k \sum_{p=1}^{P} \xi^{kp} \beta_\eta^p\right)$ building on equation (13). Panel A contains estimates of the impact of being in nonattainment for any pollutant, while Panel B shows the effect of being in nonattainment for each relevant criteria pollutant. Columns 1 and 3 include county-industry, industry-year, and nonattainment status-year fixed effects. Columns 2 and 4 replace the nonattainment status-year fixed effects with county-year fixed effects. Columns 3 and 4 include the wage and market access controls and fix their coefficient to its model-implied value. Figure D1 in the appendix shows the event study analogue of the final column and provides evidence that there are no pre-trends and that the effects on productivity persist up to five years.

In Panel A, the estimated coefficient in Column 1 is -0.074, which indicates a reduction in industry income associated with a nonattainment designation that could be arising from either increases in implicit emissions prices or decreases in productivity. The magnitude of the estimated coefficient decreases in Column 2 (-0.069) after controlling for unobservables specific to each county-year, but increases in Column 4 (-0.078) after conditioning on wages and market access and fixing their coefficients. This highlights the importance of accounting for the role of spatial and sectoral linkages in estimation. As we will see in the quantitative exercise, nonattainment designations increase real wages in attainment counties and decrease real wages in the nonmanufacturing sector, showing how nonattainment's effects spillover to untreated groups through general equilibrium channels. This, combined with the fact that nonattainment status tends to be positively spatially correlated, means our variable of interest $N_{i,t}$ is correlated with the error term in the absence of the wage and market access controls. The sign of the bias is ambiguous because the sign of the effect of the general equilibrium spillovers is ambiguous and will depend on fundamentals such as the

Table 2: Estimated effect of nonattainment on productivity.

	(1)	(2)	(3)	(4)
A. Combined				
β_T - $\theta^k \sum_{p=1}^{P} \xi^{kp} \beta_\eta^p$	-0.074^{**}	-0.069^{***}	-0.088^{*}	-0.078^{**}
	(0.031)	(0.022)	(0.049)	(0.037)
B. By Ambient Pollutant				
Carbon Monoxide Nonattainment (CO)	-0.030	-0.027	-0.066	-0.060
	(0.153)	(0.057)	(0.232)	(0.079)
Ozone/Nitrogen Dioxide Nonattainment (O_3/NO_2)	-0.064^{*}	-0.059^{**}	-0.031	-0.021
	(0.033)	(0.023)	(0.049)	(0.037)
Particulate Matter Nonattainment (PM_{10})	-0.107^{***}	-0.102^{***}	-0.171^{***}	-0.161^{***}
	(0.030)	(0.021)	(0.046)	(0.037)
Sulfur Dioxide Nonattainment (SO_2)	-0.147^{***}	-0.143^{***}	-0.155^{***}	-0.147^{***}
	(0.008)	(0.008)	(0.015)	(0.015)
Observations	72,255	72,255	72,255	72,255
Industry-County FEs	Yes	Yes	Yes	Yes
Industry-Year FEs	Yes	Yes	Yes	Yes
CO Nonattainment-Year FEs	Yes	No	Yes	No
O_3/NO_2 Nonattainment-Year FEs	Yes	No	Yes	No
SO_2 Nonattainment-Year FEs	Yes	No	Yes	No
PM_{10} Nonattainment-Year FEs	Yes	No	Yes	No
County-Year FEs	No	Yes	No	Yes
Wage and Market Access Adjustment	Omitted	Omitted	Coef. Fixed	Coef. Fixed

Notes: The table shows estimates for versions of equation (13). Each coefficient can be interpreted as a semi-elasticity, the percent change in industry income. Panel A reports estimates of the coefficient on nonattainment status determined by exceeding the regulated threshold for any pollutant. Panel B reports estimates of the coefficient on nonattainment status determined by the exceeding the threshold for the specified pollutant. Columns 1 and 3 only include industry-county, industry-year, and nonattainment-year fixed effects; Column 2 and 4 replace the nonattainment-year fixed effects county-year fixed effects, Columns 3 and 4 includes the wage and market access controls and fixes the coefficients at their theoretical value. Robust standard errors clustered at the county level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

trade elasticity.

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

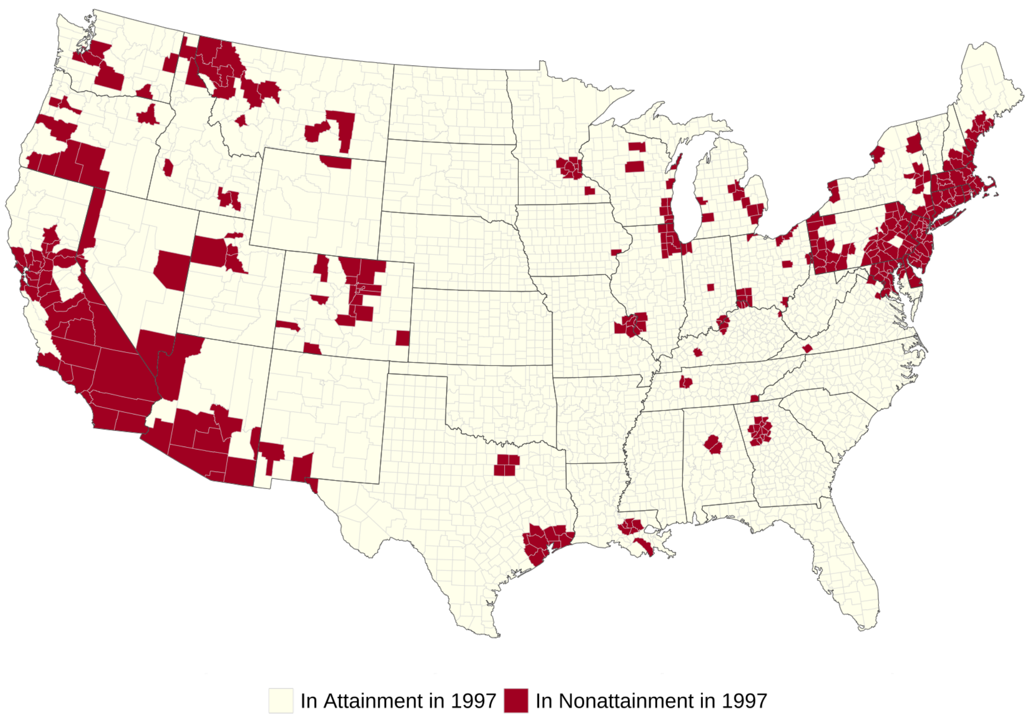
Combining estimates of $\left(\beta_T - \theta^k \sum_{p=1}^{P} \xi^{kp} \beta_\eta^p\right)$ and β_η^p, lets us back out β_T^k. For simplicity in the quantitative exercise, and given that counties can be in nonattainment for multiple types of pollutants, we will use the Table 2 estimate in Panel A and Column 4 in the counterfactuals. Our model will then capture heterogeneity in impacts on marginal costs of different kinds of pollutants, but not heterogeneity in different kinds of nonattainment designations. To recover β_T^k we first fix θ^k and ξ^{kp} to the calibrated values in Table B1. We use our preferred estimates in Tables 2 and 1 and get $\widehat{\beta_T^k} = -0.036$ which implies nonattainment induces a 3.5 percent reduction in factor productivity. We jointly bootstrap the estimates of $\left(\beta_T^k - \theta^k \sum_{p=1}^{P} \xi^{kp} \beta_\eta^p\right)$ and β_η^p at the county level 500 times to compute a non-parametric p-value of 0.136 for our estimate of $\widehat{\beta_T^k}$.This estimate of β_T^k, and the estimates of β_η^p in Table 1 Panel B Column 4 are the values we use for our quantitative exercises in the next section. If we did not condition on endogenous wages and market access in Table 2 we would obtain a β_T^k estimate of only 2.6 percent, one-fourth lower.

These results are consistent with previous research on the effect of nonattainment status under the Clean Air Act and its amendments. For example, Greenstone (2002) and Greenstone et al. (2012) use plant-level data and find that that surviving plants experienced productivity losses up to 5 percent, primarily due to standards associated with O_3 and SO_2. In addition, Walker (2013) uses longitudinal data for individual workers and finds earnings losses up to 5 percent. Although we do not follow individual workers over time, our data cover the entire United States so that, combined with our theoretical model, we are able to quantify the aggregate effects of environmental regulation.

6 Quantitative Results

With estimates of β_η^p and β_T in hand, we now we our quantitative model to conduct counterfactuals. We use 1997 as our benchmark year and choose the model parameters using estimates from the previous section or values taken from the literature. We summarize these values in Table B1 in the appendix. In our first set of results we quantify the welfare impacts of the 1997 nonattainment designations and their overall efficiency compared to the second-best pollution thresholds for assigning nonattainment designations, and the first-best emission price policy. In a second set of results we show the geographic effects of

Figure 2: All counties in nonattainment in 1997.



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

nonattainment designations and highlight the importance of general equilibrium responses.

6.1 Aggregate Impacts and Efficiency Results

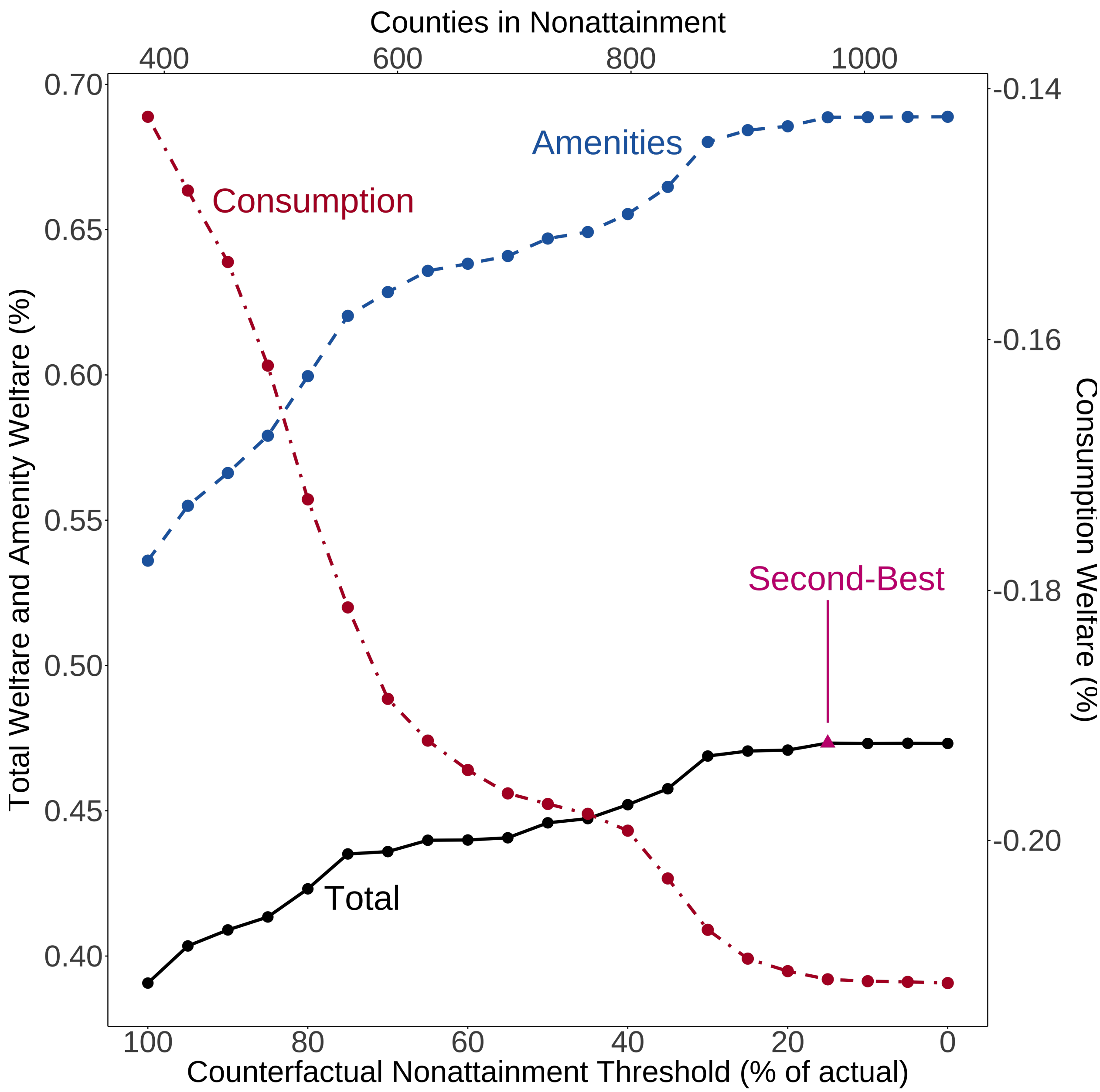
Figure 3 plots the aggregate welfare impacts of a set of nonattainment designations relative to no counties being in nonattainment (or nonattainment having no productivity or emission price effects). The left-most points on the figure correspond to the actual set of nonattainment designations in 1997 where approximately 400 counties were in nonattainment. Moving to the right on the graph increases the stringency of the concentration thresholds for nonattainment designations uniformly across pollutants. The right-most point puts every county with a pollution monitor in nonattainment.

The figure presents three new facts about the NAAQS. First, the actual set of nonattainment designations generated welfare gains of 0.39 percent in consumption-equivalent terms, which is $23 billion annually for the employed sectors. Amenities gains total 0.53 percent while consumption losses total -0.14 percent. Consumption losses only accrue to the employed sectors because the nonemployed receive a constant consumption payoff. Second, the actual set of nonattainment standards are not optimal and thus are not second-best. The welfare-maximizing NAAQS concentration standard is one-sixth of the actual concentration standard. Third, despite the large gap between the actual and second-best concentration standards, the actual set of standards achieve 80 percent of the welfare gains of the second-best policy. The figure shows that making the NAAQS more stringent generates substantial amenities improvements, but also substantial consumption losses. Eventually, both impacts level off as the marginal nonattainment county is increasingly rural and less populated so that impacts on the aggregate economy decline in magnitude.

The first six rows of Table 3 reports additional results for the welfare impacts of the actual 1997 nonattainment designations. The first two columns report total welfare, the second two columns report amenity welfare, and the last two columns report consumption welfare. The first row of the table reports the aggregate welfare impacts and matches the left-most points of Figure 3.

We further decompose the aggregate welfare effect by sector and county nonattainment status. The second row of Table 3 shows that workers in the manufacturing (polluting) sector are worse off because the welfare impacts of their consumption losses are double the size of their improvements in amenities. The third row shows that workers in the nonmanufacturing (nonpolluting) sector obtain welfare gains of nearly half a percent, or $30 billion. Their amenities gains are larger and they incur moderate reductions in consumption welfare. The fourth row shows that nonemployed workers are better off because their welfare impact is

Figure 3: Aggregate welfare impact of nonattainment designations in 1997 under different pollution concentrations for assigning nonattainment.



Note: The left y-axis reports welfare results for total welfare and amenity welfare. The right y-axis reports welfare results for consumption. The bottom x-axis is the counterfactual pollution concentration thresholds for nonattainment relative to the actual thresholds. The top x-axis indicates the number of counties in nonattainment. The solid black line reports total welfare, the dashed blue line reports amenity welfare, and the dotted red line reports consumption welfare. In this figure we only put counties with monitors in nonattainment since we do not observe pollution concentrations in counties without monitors.

Table 3: Welfare impacts of nonattainment in 1997.

	Total		Amenity		Consumption	
	%	Billion $	%	Billion $	%	Billion $
1997 Nonattainment						
Aggregate	0.39	23	0.53	40	−0.14	−17
Manufacturing	−0.21	−7	0.35	5	−0.76	−12
Nonmanufacturing	0.46	30	0.56	35	−0.07	−5
Nonemployed	0.52	–	0.57	–	–	–
Attainment Counties	0.3	5	0.29	4	0.03	1
Nonattainment Counties	0.51	18	0.77	36	−0.25	−18
Second-Best						
Aggregate	0.47	24	0.69	48	−0.21	−24
First-Best						
Aggregate	1.53	92	1.65	104	−0.11	−12

Note: Welfare is computed as the compensating variation of the observed nonattainment status in 1997 relative to a counterfactual where no counties are in nonattainment. The simulations account for impacts on emissions, factor productivity, labor reallocation, trade, and atmospheric transport of pollution. The first-best result sets the optimal nonnegative emission prices taking the implicit emission price effect of non-NAAQS regulations as given. Dollar value results do not account for welfare losses from cost of moving.

coming entirely from improved amenities.

The next two rows in Table 3 indicate that the gains primarily accrue to nonattainment counties. Nonattainment counties see welfare gains of 0.51 percent (or \$18 billion), but attainment counties have gains of 0.30 percent (or \$5 billion), about a fifth of the total welfare improvement despite not being directly affected by nonattainment. In all cases, the positive effect working through improved amenities — rather than gains or losses in consumption — accounts the for the largest portion of the overall effect as well as the effects across sectors or nonattainment status.

The bottom two rows of the table show the welfare impacts of the second-best NAAQS and the first-best emissions pricing policy relative to no counties in nonattainment. The second-to-last row repeats the right-most estimates shown in Figure 3, but also shows that the second-best outcome generates higher welfare by improving amenities more than its further worsening of consumption welfare. The last row shows that the first-best outcome generates four times the welfare gains of the actual 1997 nonattainment designations, highlighting the costs of using inefficient policy designs. Relative to 1997, the first-best policy generates over three times as much amenities improvements while actually imposing less consumption costs. Moving from the 1997 NAAQS to the first-best policy would make 99.9% of the population better off, nearly a Pareto-improvement. Figure E3 in the appendix shows that the benefits from first-best are largest in the east.

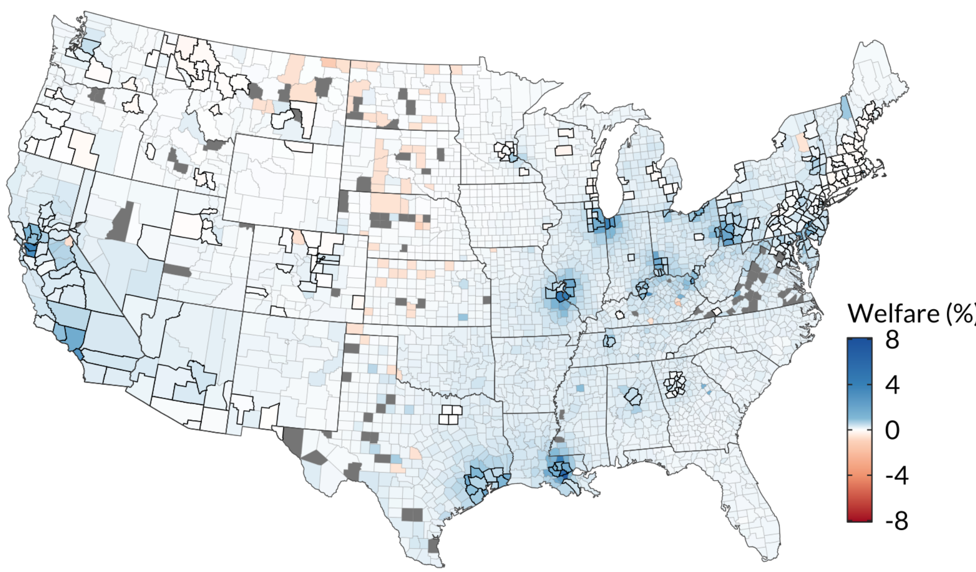
6.2 Geography and General Equilibrium Results

Section 6.1 provided evidence that nonattainment designations significantly improved welfare in the aggregate, but had heterogeneous and potentially negative effects across sectors and space. In this section we show the geography of the impacts of nonattainment designations.

Figure 4 shows our main geographic result: the spatial distribution of the welfare impacts across all counties in our sample.[23] The areas in darker shades of blue indicate progressively higher gains in contrast with areas that experience losses in red. The map provides an alternative depiction of the previous result in which nonattainment counties see large gains and reveals that there is substantial heterogeneity even within nonattainment counties. Some nonattainment counties, typically in the West, are marginally worse off, while nonattainment counties containing major cities are better off by up to 8 percent. In addition, the map makes clear that attainment counties nearby those in nonattainment in the Rust Belt and South also see substantial welfare improvements.

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

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



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

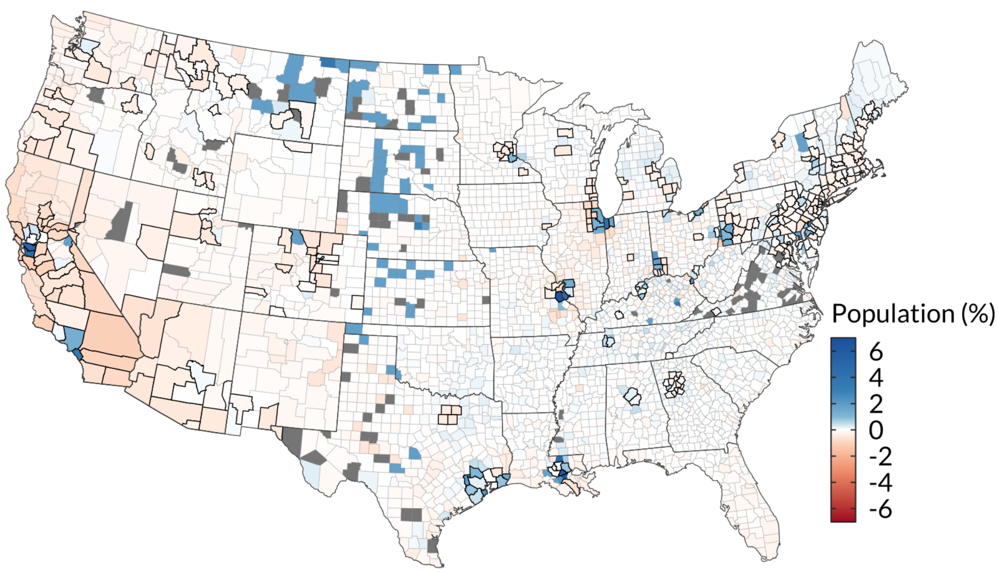
Figure 6 decomposes the welfare results on two margins. The top two maps show the welfare impact on manufacturing and nonmanufacturing. Manufacturing workers in nonattainment counties are generally worse off because nonattainment has large negative effects on their real income. Manufacturing workers in a few areas such as St. Louis and New Orleans are better off with nonattainment because counterfactually they would have been significantly more polluted. The overall spatial distribution for nonmanufacturing appears similar to the aggregate because they experience small consumption impacts and improvements in amenities are the largest component of the welfare effect.

The bottom two maps break down the aggregate welfare impact into amenity improvements and changes in consumption and real wages. The left panel shows that every county has an improvement in amenities. These benefits largely come from the significant decline in emissions in nonattainment counties leading to lower pollution concentrations everywhere. Our model suggests that there is actually a small negative leakage effect as hypothesized in Baylis et al. (2014), where emissions decline in attainment counties. The idea behind negative leakage is that the increase in the implicit emission price drives nonattainment counties to substitute away from emissions toward labor and capital. This substitution effect increases wages and rental rates in attainment counties (e.g. higher average real wages in attainment counties in Table 3), raising marginal costs of production, shrinking output and emissions in attainment counties. Negative leakage generally accounts for 0.5 percent of the aggregate emissions decline depending on the pollutant. The map also makes clear that the largest beneficiaries under nonattainment status are getting their welfare improvements almost entirely through improved amenities. The right panel shows the change in welfare caused by changes in real wages and consumption. Consumption declines in nonattainment counties but increases in most attainment counties due to the increase in nominal wages that also caused negative leakage.

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

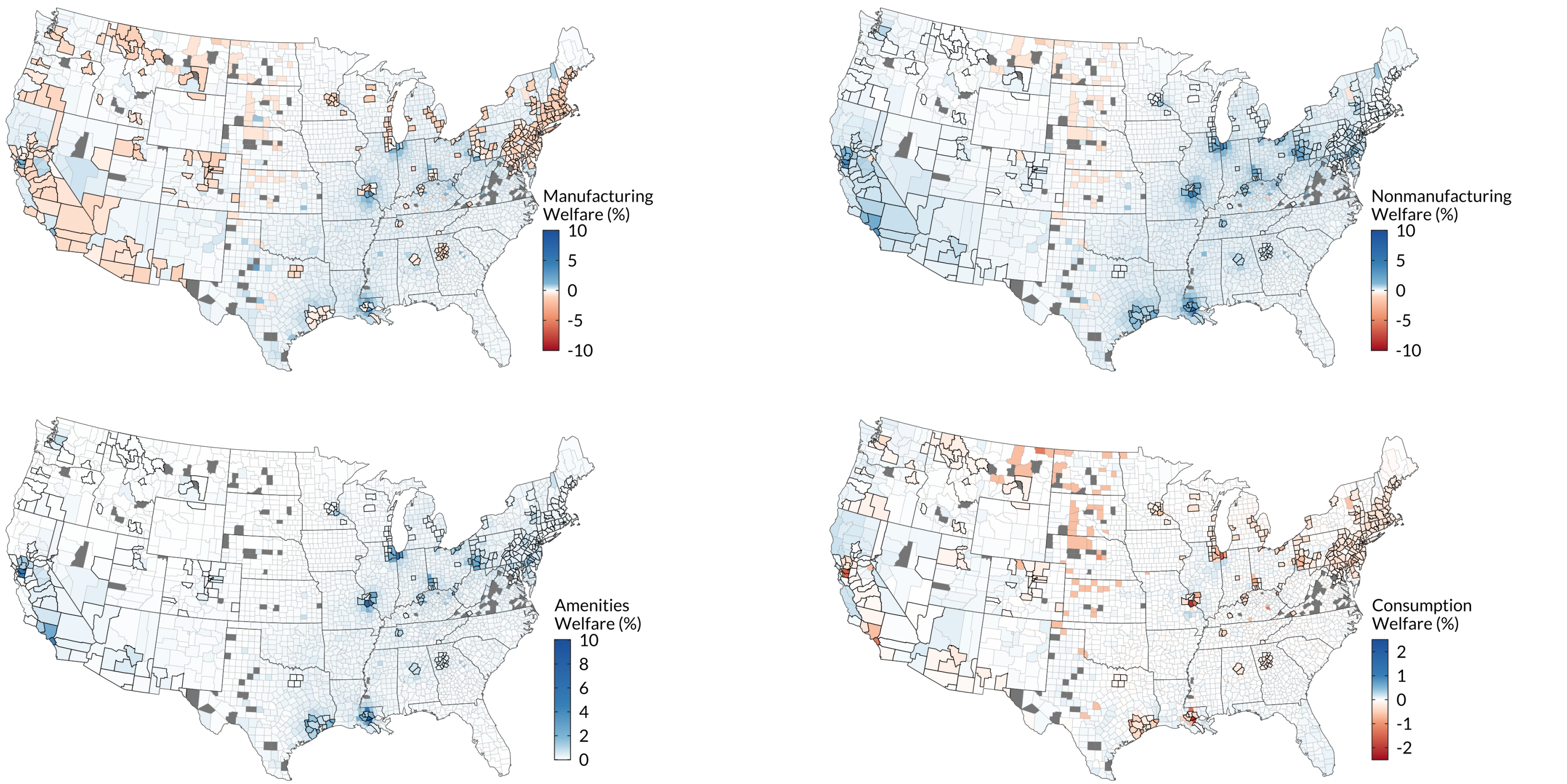
In addition to reallocation of workers across space there is also reallocation of workers across industries. Our results show that 1997 nonattainment designations reduced manufacturing employment by 1.4 percent (0.16 percentage points of the employment share); 90 percent of the displaced manufacturing workers moved into the nonmanufacturing sector and 10 percent entered nonemployment.

Figure 5: Change in population from nonattainment in 1997.



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

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



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

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7 Conclusion

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

In particular, we estimate the direct costs for firms and workers in polluting sectors from increased regulatory scrutiny and benefits to residents from reduced emissions. We combine these estimates with the full structure of the model to quantify the aggregate impact of nonattainment designations under the Clean Air Act. We find that the Clean Air Act delivers net benefits of $23 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 $700 billion.

In addition, we use the model to study the mechanisms underlying the spatial distribution of these effects. Specifically, workers are imperfectly mobile across sectors and locations, the spread of emissions is affected by atmospheric transport, and interregional trade is subject to iceberg trade costs. All of these factors potentially shape adjustments in response to changes in environmental regulation. We find that atmospheric pollution transport is particularly important in our setting. Other factors that may matter for the ultimate welfare impacts of environmental regulation include market structure, heterogeneous preferences across households, and nonhomothetic preferences over housing and particular kinds of goods. We leave these promising lines of research to future work.

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Appendix

A Amenities in Reduced Form

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

In general, we can represent B_i similarly to how we represent T_i^k in the main text:

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

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

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

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

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

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

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

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

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

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

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

A.1 The Effect of Nonattainment on Amenities

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

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

A.2 Simulating Counterfactuals with Amenities

To simulate our counterfactual we need to invert the model and solve for the level of productivity T_i^k and the implicit marginal cost of emissions η_i^{kp}. We will not need to solve for the level of amenities B_i since observed migration shares are effectively sufficient statistics for the composition of moving costs and differences in base amenities across locations.[24]

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

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

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

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

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

Next define firm market access as:

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

The two market access terms are equivalent up to a normalization so we define market access MA_i^k as:[25]

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

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

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

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

In equation (19) we must identify the market access variables MA_i^k and productivity parameters T_i^k for $k = 1, \ldots, K$. First, we can identify the MA_i^k terms. Substituting MA_i^k

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

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

into equation (18) for FMA_i^k and CMA_i^k, and that $Y_i^k = \frac{w_i^k L_i^k}{\gamma\left(1-\sum_{q=1}^{P}\xi^{kq}\right)}$ gives us:

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

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

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

We solve the model using four equilibrium conditions of the model. The first two are equations (19) and (20) along with the identity that $P_i^{k\prime} = \left(MA_i^{k\prime}\right)^{-1/\theta^k}$ The remaining conditions pin down how migration and thus the labor distribution responds to the counterfactual change in amenities $N_j' - N_j$:[26]

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

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

where the second equality assumes that the only component of amenities that is different in the counterfactual is nonattainment status, and $V_n^{0\prime} = V_n^0$. With these equilibrium conditions, we can then solve for the set of endogenous variables given any counterfactual set of nonattainment designations across counties.

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

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

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

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

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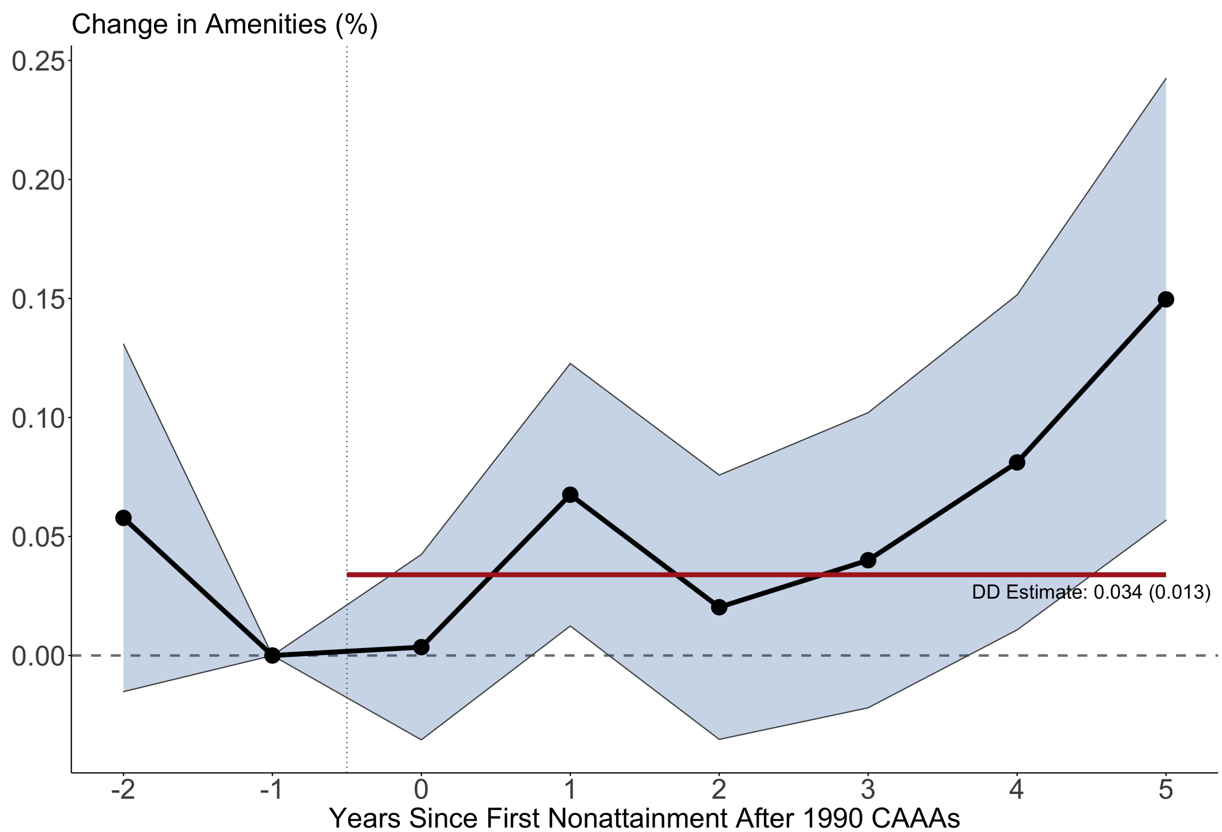
Figure A1: Difference-in-differences event study estimates of effects of nonattainment on local amenities using quasi-experimental variation from the 1990 CAAAs.



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

B Quantitative Model Parameters

Table B1: Calibrated and estimated parameter values for quantitative model.

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

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

C Welfare Derivation

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

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

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

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

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

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

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

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

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

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

D Robustness Checks

Event Study Figure D1 plots the coefficients from event study specifications that correspond on column 4 in Panel A of Table 2. This approach is similar to the approach in Walker (2013) except that we are limited to using variation in nonattainment status across polluting versus nonpolluting at the sector level rather than the plant level. The pattern of coefficients is consistent with no effect prior to nonattainment designations after 1990 and then a decrease in industry income that is statistically significant at the 1 percent level following two years of nonattainment.

Sample Periods Tables D1 and D2 present robustness checks of our main results (Panel A in both tables) with respect to the sample period. For emissions we only have one pre-period so we can only change the post-period sample. Our estimates are highly robust to the chosen years of inclusion.

Alternative Trade and Pollution Elasticities Our preferred estimate of $\left(\beta_T - \theta^k \sum_{p=1}^{P} \xi^{kp} \beta_\eta^p\right)$ from equation (13) fixed the coefficient on the real wage control variable, which depends on the value of the labor share γ, the trade elasticity θ, and the pollution elasticities ξ^{kp}. Table D3 re-estimates our preferred specification with higher and lower values of each of the three sets of parameters. Our preferred estimates are largely insensitive to these choices.

Alternative Quantitative Parameters Table D4 reports the total welfare effects of the nonattainment counterfactual scenario but under different calibrated parameter values. The first row reports the base welfare outcomes in the main text. The second two rows vary the trade elasticity and show that the quantitative values are sensitive to it, but the qualitative takeaways remain the same. The next four rows vary the consumption share parameter and the labor share parameter. The quantitative results are insensitive to their values. The remaining rows introduce congestion and agglomeration externalities. With congestion externalities, amenities can be written as:

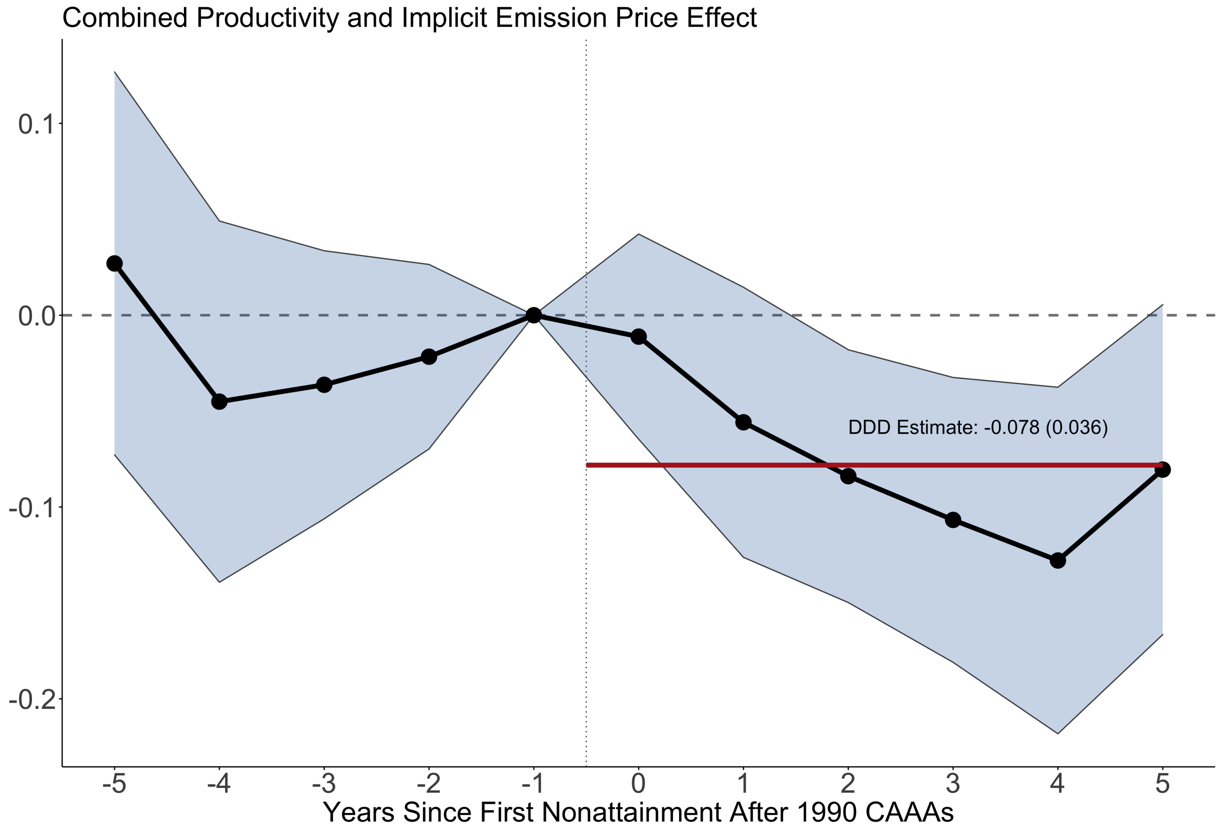
$$\tilde{B}_i = B_i L_i^{\zeta^c}$$

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

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

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

Figure D1: Event study for the effect of nonattainment on productivity and emissions prices.



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

Table D1: Difference-in-differences estimates of the effect of nonattainment on the implicit emissions price varying the sample period.

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

Robust standard errors are clustered at the county level.

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

Table D2: Triple difference estimates of the effect of nonattainment on a combination of factor productivity and implicit emissions prices varying the sample period.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_T - $\theta^k \sum_{p=1}^{P} \eta^{kp} \beta_\eta^p$	-0.079**	-0.086***	-0.088***	-0.095***	-0.078**	-0.069*	-0.061	-0.044
	(0.032)	(0.031)	(0.029)	(0.030)	(0.036)	(0.036)	(0.040)	(0.041)
Num.Obs.	60276	54289	48296	42286	66199	60147	54113	48071
Industry-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nonattainment-Year FE	No	No	No	No	No	No	No	No
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Earliest Year	1988	1989	1990	1991	1986	1986	1986	1986
Latest Year	1997	1997	1997	1997	1996	1995	1994	1993

Robust standard errors are clustered at the county level.

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

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Table D3: Triple difference estimates of the effect of nonattainment on a combination of factor productivity and implicit emissions prices varying the real wage coefficient.

	(1)	(2)	(3)	(4)	(5)	(6)
β_T - $\theta^k \sum_{p=1}^{P} \eta^{kp} \beta_\eta^p$	-0.092	-0.071**	-0.087	-0.074***	-0.079**	-0.078**
	(0.056)	(0.028)	(0.056)	(0.028)	(0.036)	(0.036)
Observations	72255	72255	72255	72255	72255	72255
Industry-County FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Nonattainment-Year FE	No	No	No	No	No	No
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Labor Share	.962	.241	.481	.481	.481	.481
Trade Elasticity	4	4	8	2	4	4
Sum of Pollution Elasticities	.018	.018	.018	.018	.036	.009

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

Table D4: Welfare impacts of nonattainment in 1997 under different model parameter values.

Parameter Change	Total %	Manuf. %	Nonmanuf. %	Attain. %	Nonattain. %
Base Parameters	*0.39*	*-0.21*	*0.46*	*0.3*	*0.51*
$\theta = 8$	0.19	-0.42	0.28	0.14	0.25
$\theta = 2$	0.99	0.31	0.97	0.89	1.17
$\alpha = 0.548$	0.39	-0.21	0.46	0.31	0.51
$\alpha = 0.137$	0.39	-0.21	0.46	0.3	0.51
$\gamma = 1$	0.42	-0.03	0.47	0.27	0.57
$\gamma = 0.2405$	0.36	-0.39	0.43	0.33	0.45
Congestion/Agglomeration	0.43	-0.45	0.56	0.29	0.59

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

E Supporting Results

Effects on Manufacturing Employment To provide further evidence of nonattainment-induced reallocation, Table E1 uses a difference-in-differences strategy to estimate the effect of nonattainment on log employment and the share of county employment in manufacturing. We find evidence that nonattainment reduces the level of manufacturing employment, and manufacturing relative to nonmanufacturing, indicating a reallocation of workers away from the regulated sector.

Welfare Value of Reallocation Figure E1 plots the welfare value of reallocation. The left map shows the value of labor reallocation, and the right map shows the value of reallocation through trade (i.e. changing market access). The aggregate effect of both is small but the left map shows that there is significant amounts of heterogeneity in the county-specific value of labor reallocation: some counties gain by nearly a half of a percent, while some counties lose by over 3 percent. The right map shows that there is very little heterogeneity for reallocation through trade.

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

First-Best Versus Actual Figure E3 plots the welfare benefits of moving from the 1997 nonattainment designations to the first-best emission price. Counties in the east benefit most from emissions pricing. The lone county worse off with emissions pricing is Weston, Wyoming.

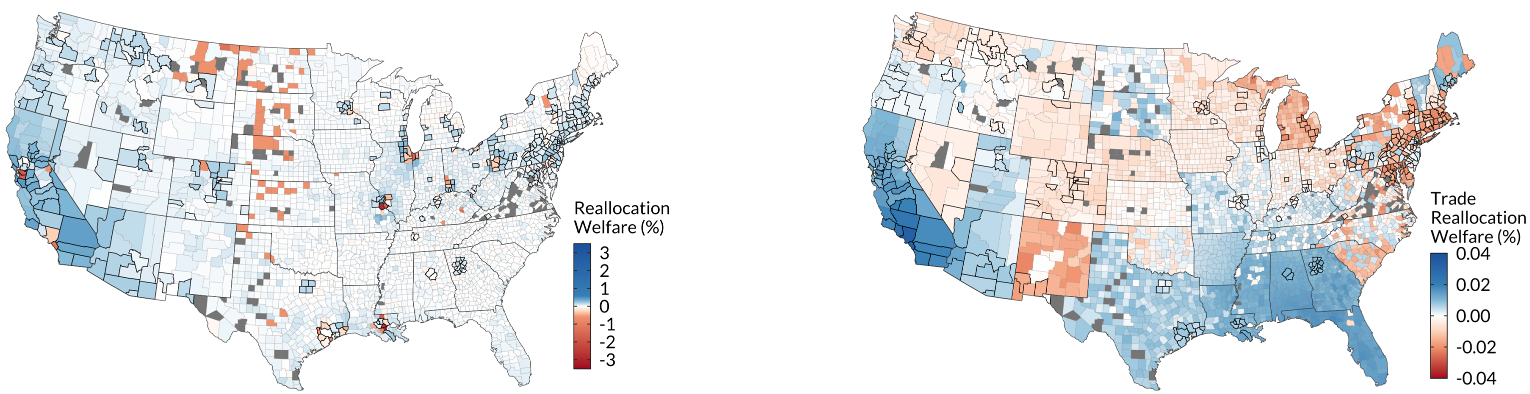
Table E1: Difference-in-differences estimates of the effect of nonattainment on log manufacturing employment and the share of county-year employment in manufacturing.

	log(Manufacturing Emp.)		Manufacturing Emp. / Total Emp.	
	(1)	(2)	(3)	(4)
1(Nonattainment)	-0.049*	-0.016	-0.010***	-0.006**
	(0.029)	(0.028)	(0.003)	(0.003)
Observations	36660	36648	36642	36630
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Market Access Control	No	Yes	No	Yes

Robust standard errors are clustered at the county level.

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

Figure E1: Value of labor reallocation and trade.



Note: The change in welfare is the difference between the model with the 1997 nonattainment statuses in effect relative to a counterfactual with no counties in nonattainment. Welfare is in terms of consumption-equivalent compensating variation and can be measured as the equivalent welfare change from a percent change in consumption. Counties outlined in a dark border are those that are in nonattainment in 1997. Grayed-out counties are omitted from the simulations because of missing data. The model includes impacts on productivity and emissions. The left panel shows the welfare impact of a model with labor reallocation to one without. The right panel shows the welfare impact of a model where market access changes endogenously to one where market access is fixed to its actual values.

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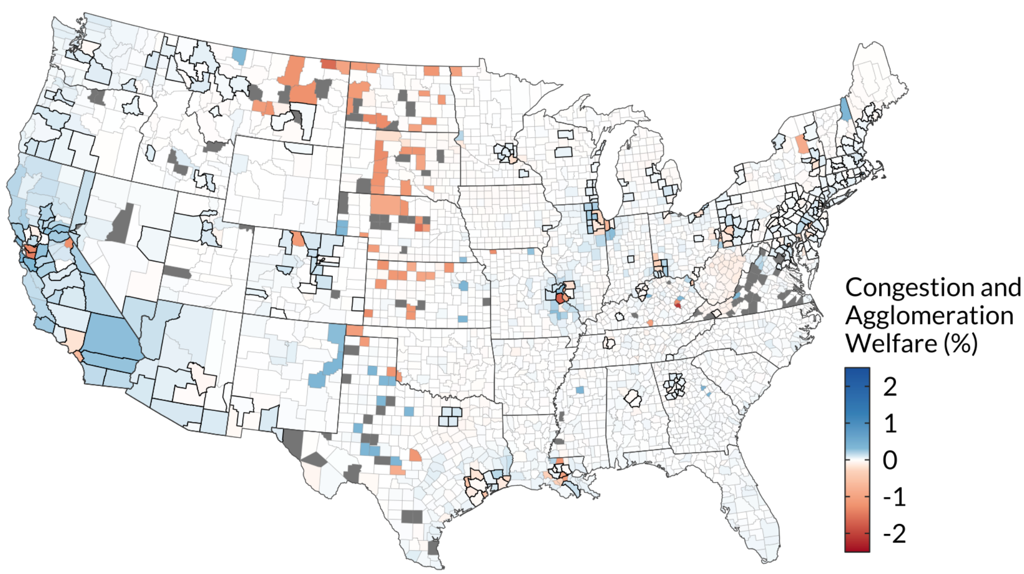
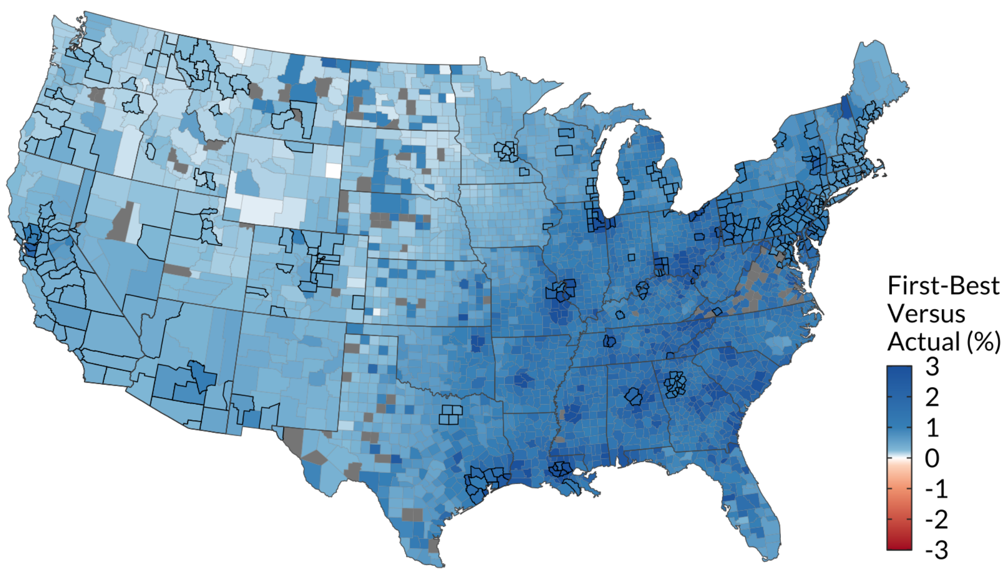
Figure E2: Value of congestion and agglomeration.



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

Figure E3: Change in county welfare from first-best relative to 1997 nonattainment.



Note: The change in welfare is the difference between the first-best relative to the model with the 1997 nonattainment status in effect. Welfare is in terms of consumption-equivalent compensating variation and can be measured as the equivalent welfare change from a percent change in consumption. Counties outlined in a dark border are in nonattainment in 1997. Grayed-out counties are omitted from the simulations due to missing data. The model includes impacts on productivity and emissions and allows for trade and labor mobility across counties and industries.