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Regional and aggregate economic consequences of environmental policy

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Abstract
This paper shows how to combine microeconometric evidence on the effects of environmental policy with a macroeconomic model, accounting for general equilibrium spillovers that have mostly been ignored in the literature. To this end, we study the effects of a recent US air pollution policy. We use regression evidence on the policy's impact across industries and local labor markets to calibrate a quantitative spatial model allowing for general equilibrium spillovers. Our model implies that the policy lowered emissions by 11.1%, but destroyed approximately 250'000 jobs. Ignoring spillovers overestimates job losses in polluting industries, but underestimates job losses in clean industries.

Key words: environmental policy, employment, trade, clean air act
JEL: E24; Q50; Q53

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1 Introduction

The costs and benefits of environmental policies are controversially debated all over the world. Opponents of these policies regularly argue that they destroy too many jobs, and hence should be watered down or abandoned outright. However, the evidence underlying these claims – or their rebuttals – is often quite limited. An informed public debate therefore requires more comprehensive estimates of the labor market impact of environmental policies. Our paper seeks to contribute to this effort, by studying the regional and aggregate economic implications of environmental policy in the United States.

Our main contribution is to combine microeconometric evidence on the effects of environmental policy with a quantitative spatial model, and thus to account for general equilibrium spillovers that have mostly been ignored in the existing literature. To this end, we study the labor market effects of a recent reform of the US Environmental Protection Agency's (EPA) air pollution regulations, targeting fine particle emissions. The paper proceeds in two steps. First, we provide regression evidence on the relative impact of the reform across industries and local labor markets. Second, we use our evidence to calibrate a quantitative spatial model, which then delivers predictions about aggregate outcomes. Our results indicate that general equilibrium effects are crucial for understanding the impact of environmental policy: ignoring them would greatly overstate job losses in polluting industries, but also miss substantial job losses in clean industries.

Our microeconometric evidence relies on a commonly used empirical strategy, leveraging the fact that air pollution regulations vary across space and time.[1] The EPA introduced fine particle regulations in 2005, setting national standards for the admissible concentration of this pollutant in the air. Counties in "non-attainment" of the standards were forced to reduce emissions, while no actions were required in attainment counties. Thus, national standards created variation in regulation that was arguably exogenous with respect to local economic shocks. We therefore assess the effects of the reform by comparing outcomes between areas that became non-attainment in 2005 and areas which did not. Given our focus on labor market outcomes, we conduct this analysis at the commuting zone level, a common measure of local labor markets (see Autor *et al.*, 2013).

Our main regression analysis relies on a triple difference specification. Intuitively, the impact of the reform should be strongest for polluting industries (i.e., industries emitting large quantities of fine particles) in non-attainment commuting zones. In line with this intuition, we show that after the reform, employment growth in polluting industries (relative

[1]This approach was first introduced by Henderson (1996). The literature review provides further details.

to “clean” industries) declined more in non-attainment than in attainment commuting zones. However, there was no significant difference in the employment growth of clean industries across commuting zones. There was also no significant difference in population growth across commuting zones, suggesting that the reform did not trigger large migration flows.

Relative employment losses in polluting industries were accompanied by lower fine particle emissions: after the reform, polluting industries in non-attainment commuting zones reduced their emissions significantly more than polluting industries in attainment commuting zones. Lower emissions appeared to be due mostly to lower emission intensity (i.e., lower emissions per worker). This suggests that industries took abatement measures to change their mode of production, rather than just reducing production volumes.

These findings are consistent with prior research, which has used similar empirical strategies to uncover negative employment effects of earlier air pollution regulations at the plant and at the worker level (Greenstone, 2002; Walker, 2013). Our results show that these negative effects extend to fine particle regulations (which had not been studied before), and that the employment losses of polluting firms do not wash out at the commuting zone level. However, our results do not pin down the change in aggregate employment. Indeed, the reform might have had negative general equilibrium effects affecting all industries and commuting zones, in which case relative differences would understate its aggregate impact. Alternatively, it might have triggered a reallocation of employment across and within commuting zones, in which case relative differences would overstate its aggregate impact.

To address these issues, we use our empirical estimates to discipline an aggregate model. Our model builds on the quantitative trade literature (Caliendo and Parro, 2015; Caliendo *et al.*, 2019), but also introduces air pollution emissions and abatement. We assume that heterogeneous commuting zones are connected through trade and migration, and industries are connected through the labor market and input-output linkages. Emission abatement, mandated by the government, directly reduces firm-level productivity. However, abatement also creates a local positive externality: lower emissions uniformly increase the productivity of all firms in a commuting zone. This externality captures the positive effects of a reduction in fine particle pollution on the health and productivity of workers.

We use our model to study an increase in abatement for polluting industries in non-attainment commuting zones. To calibrate key model parameters, we directly target four regression results: the changes in the relative emission intensity and employment of polluting industries (which jointly pin down the magnitude of the abatement shock), the fact that there are no differences in clean employment growth across commuting zones (which pins down the strength of the emission externality) and the fact that there are no differences in population growth across commuting zones (which pins down the strength of the migration response). Moreover, we consider two different values for the Frisch elasticity of labor supply, another key parameter. Our baseline calibration uses an elasticity of 2, a common value in macroeconomics (Chetty *et al.*, 2011). However, to acknowledge the substantial uncertainty around this parameter, we also consider a lower elasticity of 1.

We find that the reform reallocated activity in polluting industries through trade: as productivity and employment fell in non-attainment commuting zones, attainment commuting zones picked up some of the slack. Precisely, while polluting employment fell by 10.5% in non-attainment commuting zones, it increased by 4.1% in attainment commuting zones. Thus, general equilibrium spillovers dampen job losses in polluting industries. This effect is large: a naive extrapolation from our regression results, ignoring all spillovers, would have suggested 189'000 lost jobs in polluting industries, while our model predicts only 19'000. These results are virtually unaffected by different values for the labor supply elasticity.

Regarding clean employment, in turn, our model predicts negative spillovers. While clean industries in non-attainment commuting zones increase their productivity (through the externality from lower emissions), our calibration suggests that this effect must be small. Indeed, if it were large, clean employment should have grown faster in non-attainment than in attainment commuting zones, and this is inconsistent with our regression results. Hence, the dominating forces affecting employment in clean industries are higher prices of polluting inputs and lower labor supply due to falling real wages. Job losses caused by these spillovers (which would have been missed by a naive extrapolation from our regressions) range between 208′000 and 248′000, depending on the labor supply elasticity.

Summing up, our model thus predicts a total job loss of 267′000 with our baseline elasticity and of 228′000 with the lower value. We also find that the reform lowered fine particle emissions by 11.1%, and GDP per worker by 0.1% (due to the productivity costs of abatement). Overall, our findings show that using spatial models accounting for general equilibrium spillovers is fundamental for understanding the local and aggregate economic impact of environmental policy.

Related Literature The air pollution regulations studied in this paper go back to the landmark Clean Air Act (CAA). A large literature has analysed the impact of this law on health and economic outcomes (see Currie and Walker (2019) and Aldy *et al.* (2022) for a comprehensive overview). This literature has generally found that the CAA reduced air pollution and improved health outcomes.[2]

[2] Auffhammer *et al.* (2011) show that emission reductions are concentrated at monitors that exceeded the pollution thresholds, and Gibson (2019) points out a substitution of water pollution for air pollution. Chay and Greenstone (2003), Isen *et al.* (2017) and Bishop *et al.* (2022) provide evidence for various health benefits of the reduction in air pollution caused by the CAA.

However, researchers have also generally found a negative effect of air pollution regulation on labor market outcomes. In an influential study, Greenstone (2002) used data from the Census of Manufacturers to show that when a county switches to non-attainment, polluting plants experience lower employment, capital and sales growth (relative to non-polluting plants and attainment counties). In turn, Walker (2011, 2013) showed that employment and earnings for workers of polluting plants in counties moving into non-attainment fall relative to earnings of similar workers in attainment counties.[3]

Our empirical analysis is closely related to these studies, but considers outcomes at higher levels of aggregation and focuses on fine particle standards, which have not been studied before.[4] We find that these regulations had negative employment effects which did not wash out at the industry and local labor market level. However, our main contribution with respect to the literature is the fact that we provide an aggregate perspective, taking into account general equilibrium spillovers.

While we ultimately use a model to assess the aggregate impact of air pollution regulations, our conclusions are guided by our empirical analysis. Indeed, we calibrate several key elasticities to match our regression results, using the latter as "identified moments" (Nakamura and Steinsson, 2018). Recently, researchers have used similar approaches to evaluate the aggregate effects of industrial robots or import competition from China (Acemoglu and Restrepo, 2020; Caliendo *et al.*, 2019; Rodríguez-Clare *et al.*, 2020). Our paper is also related to a growing literature using spatial equilibrium models to assess the effects of climate change (see e.g. Rudik *et al.*, 2022; Bilal and Rossi-Hansberg, 2023; Cruz and Rossi-Hansberg, 2024). Most closely related to our paper are Shapiro and Walker (2018) and Hollingsworth *et al.* (2022). Shapiro and Walker (2018) structurally estimate a trade model to decompose the fall of air pollution in US manufacturing. They find that tighter regulation was the main driver of lower emissions. Hollingsworth *et al.* (2022) analyse the welfare implications of a 1990 amendment of the CAA. Using panel regressions, they estimate the productivity losses caused by this reform, and then feed these into a trade model. They find that the reform improved welfare, but that a first-best policy could have achieved much higher gains. Both papers assume full employment. Instead, our focus is on the employment impact of environmental regulations. In particular, we directly link

[3]Likewise, Henderson (1996) finds a negative effect of the CAA on the number of polluting plants, List *et al.* (2003) find a negative effect on plant entry, and Greenstone *et al.* (2012) find a negative effect on manufacturing productivity. Kahn and Mansur (2013), in turn, find mixed results for the effect of the CAA on employment using a border county design. Obviously, negative employment effects must be compared to the positive health impact. According to Currie and Walker (2019), "*current estimates suggest that the overall costs are likely to have been substantially less than the estimated benefits in terms of health and other outcomes*".

[4]Bishop *et al.* (2022) use the same reform to show that fine particle exposure increases the risk of dementia.

microeconometric regression evidence on employment effects to a macroeconomic model, using the identified coefficients from the former to calibrate the latter.[5]

The remainder of this paper is structured as follows. Section 2 describes the institutional background and our data. Section 3 analyses the impact of fine particle regulations across industries and commuting zones. Section 4 lays out the model, and Section 5 describes its calibration. Section 6 presents our quantitative results, and Section 7 concludes.

2 Institutional background and data

2.1 The Clean Air Act and regulation of fine particle emissions

The Clean Air Act, passed in 1970, is "*arguably the most important and far-reaching environmental statute enacted in the United States*" (Aldy *et al.*, 2022). Among many other provisions, it empowered the EPA to set National Ambient Air Quality Standards (NAAQS) for several pollutants, including sulfur dioxide (SO_2), nitrogen oxides (NO_x), carbon monoxide (CO) or particulate matter (including fine particles, $PM_{2.5}$).

The NAAQS set threshold values for the atmospheric concentration of each regulated pollutant, based on public health considerations. Using data from monitoring stations, the EPA determines once a year whether counties are in attainment of these thresholds. State governments must then present an "Implementation Plan" for their non-attainment counties, explaining how they will reduce emissions of the pollutants exceeding the thresholds. Typical measures include mandates for air filters or emission trading schemes. The EPA can also directly impose regulations on non-attainment counties, e.g. by requiring plants to adopt technologies with the "lowest achievable emissions rate".

Crucially, both the thresholds and the pollutants included in the NAAQS change over time. Our paper focuses on fine particles, which have seen the most regulatory changes in the last decades. Prompted by increasing evidence for the negative health consequences of fine particle exposure (which can cause or amplify several heart and lung conditions),[6] the EPA set the first NAAQS thresholds for this pollutant in 1997.[7] Implementation started in January 2005, when counties were first classified as attainment or non-attainment. Thresholds were tightened in 2006 (implemented in 2009) and 2012 (implemented in 2015).[8]

[5] The EPA also commissions model-based evaluations of the CAA (see e.g. Goettle *et al.*, 2007). However, these also assume full employment and are not calibrated to the empirical evidence.

[6] The Global Burden of Disease project has estimated that fine particles caused 47'800 deaths in the United States in 2019 (see https://www.healthdata.org/research-analysis/gbd).

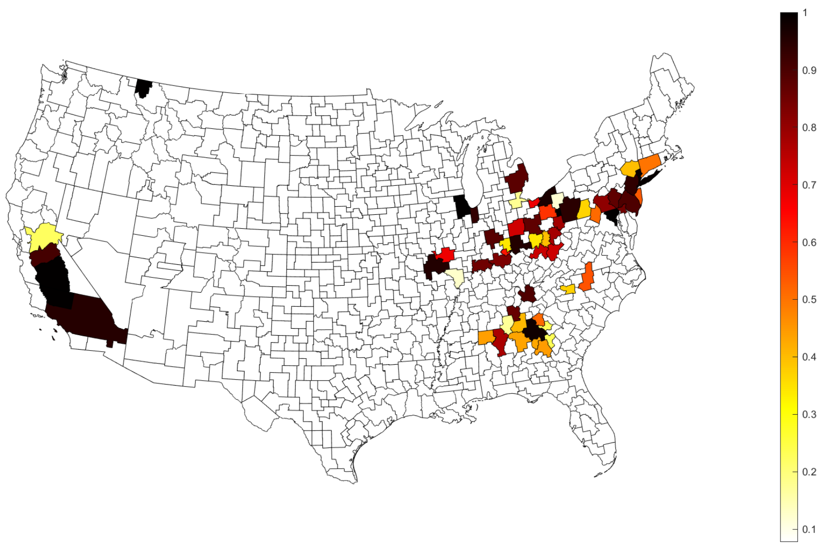
[7] Previously, only larger particles, such as total Total Suspended Particulates (TSP) or PM_{10} were regulated.

[8] A timeline of the NAAQS for fine particles is available at https://www.epa.gov/pm-pollution/

We focus throughout on the initial attainment classification, and refer to this event as "the reform". Moreover, following Bishop *et al.* (2022), we consider 2004 as the effective reform date. Indeed, initial attainment status in 2005 was based on atmospheric concentrations measured between 2001 and 2003, so that by early 2004, state governments knew the future attainment status of each county.

We obtain data for the attainment status of counties from the EPA's Green Book. However, given our focus on local labor markets, we conduct our analysis at the commuting zone level rather than at the county level. We map counties to commuting zones using the correspondence table of Chetty *et al.* (2014). For our baseline analysis, we measure the attainment status of a commuting zone by the fraction of its population living in counties classified as wholly or partially non-attainment. Population shares are measured in 2003 (the pre-reform year). Our results are robust to alternative definitions.

Figure 1: The geographical scope of the EPA's fine particle regulations



Notes: This map shows the share of the population living in non-attainment counties for all US commuting zones, excluding Alaska and Hawai'i. In non-shaded commuting zones, all counties were in attainment.

As Figure 1 shows, 62 commuting zones (out of a total of 741) had at least one non-attainment county. Clearly, non-attainment status was not randomly assigned: as shown in Table A.1 in the Appendix, non-attainment commuting zones tend to be larger and more urban. Nevertheless, there is substantial variation across large commuting zones. For instance, the share of the population living in non-attainment counties was 100% in

timeline-particulate-matter-pm-national-ambient-air-quality-standards-naaqs.

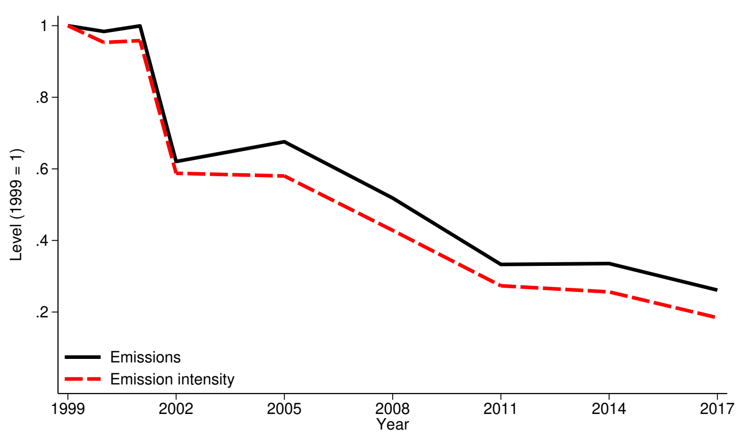
Chicago, 99% in New York and 95% in Los Angeles, but 0% in Miami, Boston or Dallas. Moreover, non-attainment status depends on persistent local characteristics: indeed, no county ever switches into non-attainment in a year without NAAQS changes. In our regressions, we control for these time-invariant commuting zone-industry characteristics (as well as for industry and commuting zone-level time trends) through fixed effects.[9]

2.2 Fine particle emissions

We obtain plant-level data for primary fine particle emissions from the EPA's National Emissions Inventory (NEI).[10] We then aggregate this data to the commuting zone-industry level, where industries are defined by 3-digit NAICS codes. Data is available yearly from 1999 to 2002, and in three-year intervals between 2002 and 2017.

Figure 2 summarizes aggregate emission trends between 1999 and 2017 (summing across all industries and commuting zones). Fine particle emissions declined by 74% over the period, while emissions per unit of real value added fell by 82%.

Figure 2: Trends in fine particle emissions



Notes: This figure plots aggregate fine particle emissions (black solid line) and emissions per unit of real value added (red dotted line). Aggregate figures are obtained by summing emissions across all industries and commuting zones. Both series are normalized to 1 in 1999.

Fine particles are mainly created through the combustion of gasoline, oil, diesel fuel or wood. Thus, emissions are concentrated in a few industries. For our baseline analysis,

[9] In 16 commuting zones, all counties were attainment in 2005, but at least one county moved into non-attainment with the tighter 2009 standards. We omit these commuting zones in our empirical analysis, in order to avoid the issues caused by staggered treatment (see Borusyak *et al.*, 2024).

[10] The NEI contains two measures of fine particle emissions, primary and filterable emissions. As their name indicates, filterable emissions can be captured on an air filter. Primary emissions are the sum of filterable and condensable emissions, the latter being emissions that originate as gases and condense into fine particles later. We focus on primary emissions both because they are more comprehensive, and because the data is less noisy.

we consider industries as "polluting" if they represent more than 4% of national emissions in 1999 (the first year with emissions data). There are six such industries: Utilities (NAICS Code 221), Paper products (322), Primary metals (331), Non-metallic minerals (327), Chemicals (325) and Wood Products (321). Together, they accounted for over 82% of industrial fine particle emissions in 1999.[11] Thus, it is reasonable to assume that the reform's direct effect was concentrated in these polluting industries. In contrast, industries that hardly emit any fine particles (such as services) can only have been indirectly affected.

2.3 Employment, population, and commuting zone characteristics

To measure the reform's impact on jobs, we use annual employment data at the county-industry level from Eckert *et al.* (2020), based on the Census Bureau's County Business Patterns (CBP). This dataset covers the period from the mid-1970s to 2016, and we focus on the period 1995-2016. We again define industries at the 3-digit NAICS level, and aggregate county data to commuting zones using the correspondence table of Chetty *et al.* (2014).

We also use annual data on county population from the Census Bureau. Finally, we rely on data compiled by Chetty *et al.* (2014) to capture persistent commuting zone characteristics, such as exposure to Chinese import competition, trend income growth, labor force participation or the fraction of foreign-born inhabitants. Appendix A contains more details on all data sources, and Appendix Tables A.2 and A.3 show summary statistics.

3 Empirical analysis

3.1 The effect of fine particle regulations on employment

We start by analysing the effects of the reform on employment, our main outcome of interest. To do so, we rely on a triple difference specification which has been extensively used in the literature (e.g. Greenstone, 2002; Walker, 2013). This is based on the simple idea that the effect of the EPA regulations should be most prominent after the reform (first difference), in non-attainment relative to attainment commuting zones (second difference), and for polluting relative to clean industries (third difference). Accordingly, we estimate

$$\ln L_{n,t}^{j} = \sum_{y=1995}^{2016} \gamma_y \cdot \left(S_n^{\mathrm{NA}} \cdot \mathrm{Emit}_{1999}^{j} \cdot \mathbb{1}_{y,t} \right) + \alpha_n^j + \alpha_t^j + \alpha_{n,t} + \epsilon_{n,t}^{j}. \tag{1}$$

[11] As shown in Figure A.1 in the Appendix, industrial production accounted for 69% of all fine particle emissions in the United States in 1999. The second most important source, at 24%, was transportation.

In this specification, $L^j_{n,t}$ is employment in commuting zone n and industry j in year t. S^{NA}_n is the share of commuting zone n's population living in counties designated as non-attainment by the reform. Emit^j_{1999} is a dummy for polluting industries, and $\mathbb{1}_{y,t}$ is a dummy for year y. The coefficients of interest in this regression are the (year-specific) coefficients for the interaction between commuting zone non-attainment status and the polluting industry dummy, γ_y. For instance, more negative coefficients after the reform would imply that in non-attainment commuting zones (relative to attainment commuting zones), polluting industries experience a decline in employment relative to clean ones. The specification controls for commuting zone-industry, industry-year and commuting zone-year fixed effects (and thus for any industry or commuting zone specific time trends). We weight observations by commuting zone-industry employment in 1995, and cluster standard errors by state.[12]

Figure 3: Relative employment of polluting industries in non-attainment commuting zones

Notes: The solid black line plots the coefficients γ_y for the model specified in equation (1). Red dashed lines indicate 90% confidence intervals. Observations are weighted by commuting zone-industry employment in 1995, and standard errors are clustered by state. The green vertical line indicates the pre-reform year, 2003.

Figure 3 illustrates the results for this regression. The solid black line plots our estimates for the coefficient γ_y for every year y, while the red dotted lines show 90% confidence intervals. As discussed above, EPA regulations were effectively introduced in early 2004. Thus, we consider 2003 as the pre-reform year, and normalize outcomes to zero in this year by dropping the corresponding interaction variable. The figure shows a stark reversal of trend in the years around the reform. Prior to the reform, in non-attainment commuting zones

[12]We drop commuting zone-industry pairs which do not have observations for all years of the sample. Finally, we winsorize the absolute value of annual employment growth at 0.69 log points (corresponding to changes by a factor of 1/2 or 2, and roughly to the 1st and 99th percentiles of employment growth in the data). We then re-compute log levels of employment to be consistent with these winsorized growth rates.

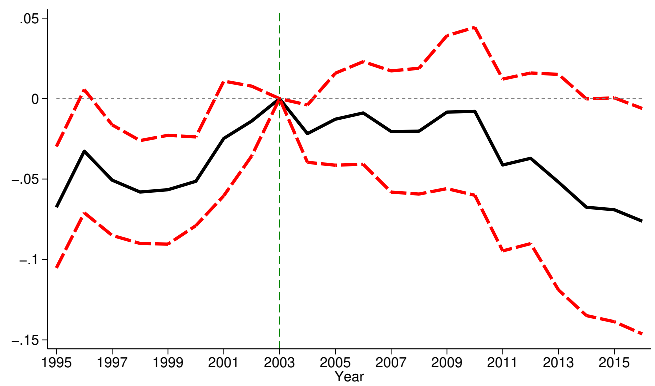
(relative to attainment commuting zones) employment grew more strongly in polluting industries than in clean industries. After the reform, however, this trend was reversed, and there was a relative decline in the employment of polluting industries in non-attainment commuting zones, reaching about 8 log points by 2016.

Next, we analyse whether the reform also affected employment in clean industries. To do so, we drop the commuting zone-year fixed effects in equation (1) and replace them with the interactions between the non-attainment variable and year dummies. That is, we estimate

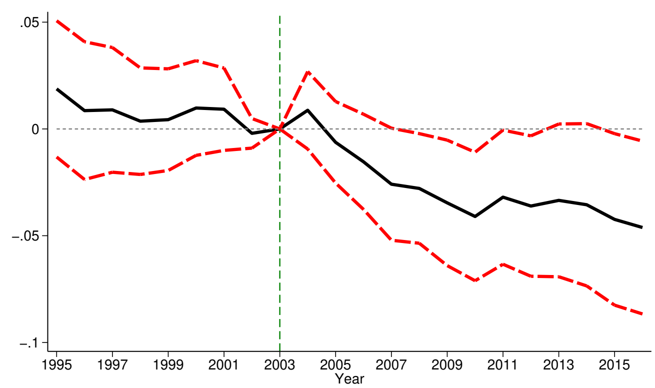
$$\ln L_{n,t}^{j} = \sum_{y=1995}^{2016} \gamma_y \cdot \left(S_n^{\mathrm{NA}} \cdot \mathrm{Emit}_{1999}^{j} \cdot \mathbb{1}_{y,t} \right) + \sum_{y=1995}^{2016} \delta_y \cdot \left(S_n^{\mathrm{NA}} \cdot \mathbb{1}_{y,t} \right) + \alpha_n^j + \alpha_t^j + \epsilon_{n,t}^j. \quad (2)$$

Figure 4: Relative employment in non-attainment commuting zones

Panel (a): Polluting industries (Triple interaction coefficients γ_y)



Panel (b): All industries (Interaction coefficients δ_y)



Notes: Panel (a) shows the coefficients γ_y and panel (b) the coefficients δ_y from an estimation of the model specified in equation (2). Red dashed lines indicate 90% confidence intervals. Observations are weighted by commuting zone-industry employment in 1995, and standard errors are clustered by state.

Figure 4 plots the results for the coefficients γ_y and δ_y. Our results for the coefficients on the triple interactions, γ_y, are shown in panel (a). They are very similar to the ones in the baseline in Figure 3, still indicating a relative post-reform decline of polluting employment in non-attainment commuting zones. The coefficients δ_y, in turn, capture changes in employment for all industries in non-attainment relative to attainment commuting zones. Our estimates, shown in panel (b), suggest that non-attainment commuting zones experienced an overall decline in employment. However, this finding might be driven by pre-trends: indeed, their relative employment was already declining before the reform.

The pre-trends in Figure 4 could be explained by the fact that non-attainment status was not randomly assigned. For instance, as discussed in Section 2, more urban commuting zones were more likely to be non-attainment, but they might also have been on different employment trends for reasons unrelated to EPA regulations. To address this issue, we consider a specification in first differences, comparing employment growth before and after the reform. This controls for any long-run differences in employment growth between attainment and non-attainment commuting zones, and checks whether the differences in trends before and after the reform shown in Figures 3 and 4 are significant. We estimate

$$\ln L^j_{n,t} - \ln L^j_{n,t-1} = \gamma_L \cdot \left(S^{\text{NA}}_n \cdot \text{Emit}^j_{1999} \cdot \mathbb{1}^{\text{Post}}_t \right) + \alpha^j_n + \alpha^j_t + \alpha_{n,t} + \epsilon^j_{n,t}, \tag{3}$$

where $\mathbb{1}^{\text{Post}}_t$ is a dummy equal to 1 if t is a post-reform year (i.e., 2004 or later).

The first column of Table 1 shows the results for the specification in equation (3). To interpret these results, consider a commuting zone in which the entire population lives in non-attainment counties (such that $S^{\text{NA}}_n = 1$). Our estimate shows for such a commuting zone, the annual employment growth rate in polluting industries (with respect to clean ones) was about 1.2 log points lower after the reform than for an attainment commuting zone. This is a substantial effect, adding up to 15.6 log points (or 14.4%) over the 13-year long post-reform period 2004-2016. This magnitude is in line with the empirical evidence on earlier air pollution regulations.[13]

Column (2), in turn, considers the analogue to Figure 4, dropping commuting zone-year fixed effects and replacing them with the interaction between the non-attainment variable S^{NA}_n and the post-reform dummy $\mathbb{1}^{\text{Post}}_t$. As was already apparent from Figure 4, this coefficient is only slightly negative and not significantly different from zero. This suggests that the overall employment growth rate of non-attainment relative to attainment commuting zones did not change after the reform. As the large majority of workers (more than 95%) work in clean industries, this implies that the reform had at most a small negative effect on the relative employment of clean industries in non-attainment commuting zones.

[13] Walker (2013), who studies the 1990 amendment of the CAA with a similar triple difference strategy, finds a relative employment loss of about 20 percentage points over 10 years for polluting industries.

Table 1: The effect of fine particle regulations on employment growth

	(1)	(2)	(3)	(4)	(5)	(6)
$S_n^{\text{NA}} \cdot \text{Emit}_{1999}^j \cdot \mathbb{1}_t^{\text{Post}}$	-0.012***	-0.014***	-0.015***	-0.009**	-0.011***	-0.011***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
$S_n^{\text{NA}} \cdot \mathbb{1}_t^{\text{Post}}$		-0.001	0.003		-0.001	0.002
		(0.002)	(0.004)		(0.002)	(0.003)
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
CZ-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
CZ-year FE	Yes	No	No	Yes	No	No
N	851571	851592	838698	851571	851592	838698
R^2	0.298	0.263	0.264	0.298	0.263	0.264

Notes: Column (1) shows our estimates for the parameter γ_L in equation (3). Columns (2) drops commuting zone-year fixed effects $\alpha_{n,t}$ and instead introduces the interaction $S_n^{\text{NA}} \cdot \mathbb{1}_t^{\text{Post}}$. Column (3) adds five control variables to the specification from Column (2), all interacted with $\mathbb{1}_t^{\text{Post}}$: a dummy for urban commuting zones, the increase in imports from China between 1990 and 2000, income growth between 2000 and 2010, the labor force participation rate, and the percentage of foreign-born inhabitants. Columns (4)-(6) repeat Columns (1)-(3), replacing the non-attainment variable S_n^{NA} with a dummy equal to 1 if at least one third of the commuting zone's population lives in a non-attainment county. The dependent variable is winsorized to be between -0.69 and 0.69 log points. Observations are weighted by commuting zone-industry employment in 1995. Standard errors clustered by state in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We consider results from column (2) as our baseline, and will rely on them to calibrate our model. Using these estimates, we could already compute a naive estimate for the employment loss caused by the reform, ignoring all general equilibrium spillovers (i.e., assuming that employment in attainment commuting zones is unaffected by the reform). However, in the presence of spillovers, this naive estimate could be severely biased. We will come back to this issue in our quantitative analysis in Section 6.

Before proceeding, columns (3) to (6) of Table 1 show robustness checks. Column (3) introduces controls for long-run differences between commuting zones (interacted with the post-reform dummy and taken from Chetty *et al.*, 2014): a dummy for urban commuting zones, the increase in imports from China between 1990 and 2000, trend income growth (measured between 2000 and 2010), labor force participation, and the percentage of foreign-born inhabitants. This does not affect our estimates. Finally, columns (4)-(6) replace our non-attainment variable by a dummy equal to 1 when more than a third of the commuting zone's population lives in non-attainment counties, as in Vona *et al.* (2019). Again, results are similar to our baseline. Appendix Tables A.4 and A.5 contain further robustness checks, including different reform dates and different measures of polluting industries.

3.2 Emissions and emission intensity

Next, we analyze the effect of the reform on fine particle emissions. This is interesting in its own right, and will also be useful for estimating the magnitude of abatement shocks in our quantitative model. To study emissions, we concentrate on polluting industries, using a difference in difference strategy.[14] Intuitively, we expect that after the reform, emissions of polluting industries fall more strongly in non-attainment commuting zones. To test this hypothesis, we estimate

$$\frac{1}{3}\left(\ln E^{j}_{n,t} - \ln E^{j}_{n,t-3}\right) = \gamma_E \cdot \left(S^{\text{NA}}_{n} \cdot \mathbb{1}^{\text{Post}}_{t}\right) + \alpha^{j}_{n} + \alpha^{j}_{t} + \epsilon^{j}_{n,t}, \tag{4}$$

where $E^{j}_{n,t}$ stands for fine particle emissions of industry j in commuting zone n in year t. As emissions are only observed in 3-year intervals after 2002, we consider three-year growth rates (annualized to make scales comparable to our employment regressions in Section 3.1). All other variables are defined as before.[15] We estimate this equation with data from polluting industries, and weight observations by emissions in 1999.

Table 2: The effect of fine particle regulations on emissions

	(1)	(2)	(3)	(4)	(5)	(6)
$S^{\text{NA}}_{n} \cdot \mathbb{1}^{\text{Post}}_{t}$	-0.074**	-0.077**	-0.082**	-0.085**	-0.054	-0.059**
	(0.036)	(0.032)	(0.038)	(0.034)	(0.033)	(0.029)
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
CZ-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	7458	7422	5250	5214	7458	7422
R^2	0.256	0.260	0.251	0.254	0.256	0.260

Notes: Column (1) shows our estimates for γ_E in the specification in equation (4). Columns (2) adds our control variables for persistent commuting zone characteristics defined in Table 1. Columns (3)-(4) limit the sample to the four most polluting industries, and columns (5)-(6) consider the dummy measure of commuting zone attainment status defined in Table 1. Columns (3) and (5) do not use controls, while columns (4) and (6) include the same control variables as in column (2). The dependent variable is winsorized between -0.69 and 0.69 log points. Observations are weighted by commuting zone-industry emissions in 1999. Standard errors clustered by state in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 2 shows the results from this regression. Column (1), which contains the baseline

[14] A triple difference analysis as in Section 3.1 is inappropriate here: as clean industries emit no or little fine particles, they are not a meaningful comparison group.

[15] Accordingly, we consider emissions growth between 2002 and 2005 as being post-reform. However, as shown in Tables A.6 and A.7 in the Appendix, our results do not change when we omit data for this period.

specification, shows a large and significant drop in emissions. Consider again a commuting zone in which the entire population lives in non-attainment counties. For the average polluting industry in this commuting zone, emissions fell by 7.4 log points more in each year after the reform than for the same industry in an attainment commuting zone.

Columns (2) to (6) of Table 2 consider robustness checks. In column (2), we introduce the same control variables as in our analysis for employment. Columns (3)-(4) limit the sample to the four most polluting industries (utilities, paper, primary metals and non-metallic minerals). Column (3) does not use control variables, while column (4) does. Our point estimates are somewhat larger in this sub-sample, indicating that the more polluting industries experienced greater reductions in emissions. Finally, columns (5)-(6) use the dummy measure for commuting zone non-attainment status introduced in Table 1.

Lower emissions can be achieved either through lower production, or through lower emissions per unit of output. Using employment as a proxy for production, and comparing Tables 1 and 2, we note that we find much larger reductions in emissions than in employment.[16] This suggests that emission reductions were mostly due to lower emission intensity. To test this formally, Table 3 shows estimation results when replacing the dependent variable in equation (4) by the growth rate of emissions per worker.

Table 3: The effect of fine particle regulations on emission intensity

	(1)	(2)	(3)	(4)	(5)	(6)
$S_n^{\text{NA}} \cdot \mathbb{1}_t^{\text{Post}}$	-0.078*	-0.083**	-0.087*	-0.092**	-0.060	-0.066*
	(0.041)	(0.037)	(0.044)	(0.040)	(0.037)	(0.034)
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
CZ-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	7407	7371	5212	5176	7407	7371
R^2	0.241	0.244	0.238	0.241	0.241	0.244

Notes: All specifications in this table are the same as in Table 2, but use emission intensity (emissions per worker) as the dependent variable. Employment data ends in 2016, while emissions data ends in 2017. Thus, we use 2016 employment levels to compute emission intensities for 2017. The dependent variable is winsorized between -0.69 and 0.69 log points. Observations are weighted by commuting zone-industry emissions in 1999. Standard errors clustered by state in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Results in Table 3 are similar to those in Table 2. They indicate that for polluting industries in non-attainment commuting zones, emission intensity fell after the reform, presumably because of abatement measures imposed by the EPA and state governments.

[16]Ideally, we would want to observe physical output or sales. However, there is no data for these variables at the commuting zone-industry level, and we therefore need to use employment as a proxy.

3.3 Population

Finally, we analyse whether the reform led to changes in commuting zone population. We rely on a difference-in-difference regression and estimate:

$$\ln \text{Pop}_{n,t} - \ln \text{Pop}_{n,t-1} = \gamma_{\text{Pop}} \cdot \left(S_n^{\text{NA}} \cdot \mathbb{1}_t^{\text{Post}} \right) + \alpha_n + \alpha^j + \epsilon_{n,t}. \tag{5}$$

Our results, shown in Table 4, indicate that there is no significant change in the relative population growth of non-attainment commuting zones after the reform. Hence, the reform does not appear to have triggered a large migration response. Appendix B contains further results at the commuting zone level, for both emissions and employment.

Table 4: Population growth in non-attainment commuting zones

	(1)	(2)	(3)	(4)
$S_n^{\text{NA}} \cdot \mathbb{1}_t^{\text{Post}}$	-0.000	0.004	-0.000	0.003
	(0.002)	(0.003)	(0.001)	(0.003)
CZ FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	15225	14847	15225	14847
R^2	0.272	0.291	0.272	0.290

Notes: Column (1) shows our estimate for γ_{Pop} in equation (5). Column (2) adds our controls for commuting zone characteristics defined in Table 1. Columns (3)-(4) use a dummy measure for a commuting zone's non-attainment status, also defined in Table 1. Observations are weighted by commuting zone population in 1995. Standard errors clustered by state in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Summing up, our empirical analysis finds that the reform had a negative effect on the relative emissions and employment of polluting industries. On the other hand, employment growth in clean industries and population growth were no different in attainment and non-attainment commuting zones. However, while these relative outcomes are informative, they do not speak directly to the aggregate impact of the EPA's actions. To quantify this aggregate impact, we now introduce a model that accounts for general equilibrium forces.

4 Model

Our model builds on the recent literature on quantitative trade models with labor mobility (e.g. Caliendo *et al.*, 2019). We add several new elements to this framework, most importantly, air pollution emissions and abatement.

4.1 Assumptions

Households We consider an economy made up of N commuting zones and J different industries, and populated by a continuum of households with mass 1.

Each household h needs to take two decisions. First, she needs to choose a commuting zone-industry pair (n, j) in which to live and work. Second, she needs to choose how much labor to supply in this commuting zone and industry. Her utility is given by

$$u(h) = \max_{n,j} \left[\iota_n^j + \eta_n^j(h) + \max_{\ell_n^j(h)} \left[\ln \left(\frac{1}{1-\chi} \left(c_n^j(h) \right)^{1-\chi} - \frac{\zeta}{\zeta+1} \left(\ell_n^j(h) \right)^{\frac{\zeta+1}{\zeta}} \right) \right] \right], \tag{6}$$
$$\text{such that } \; P_n c_n^j(h) = w_n^j \ell_n^j(h).$$

In this expression, $c_n^j(h)$ stands for the household's consumption, expressed in units of the unique final consumption good of the commuting zone she lives in, and $\ell_n^j(h)$ stands for her labor supply. Labor supply depends on the prevailing wage in the commuting zone-industry pair, w_n^j, the price of the final consumption good in the commuting zone, P_n, and parameters $\chi \in (0, 1)$ and $\zeta > 0$. ζ is the Frisch elasticity of labor supply and will play an important role in our analysis.

Additionally, the optimal location choice depends on the level of amenities of a commuting zone-industry ι_n^j (a positive parameter) and the idiosyncratic preference of a household for this commuting zone-industry, $\eta_n^j(h)$. Following Rodríguez-Clare *et al.* (2020), we assume that each household draws a vector of idiosyncratic preferences $\boldsymbol{\eta} \equiv \left[\eta_1^1, ..., \eta_N^J\right]$ from a nested Gumbel distribution with a joint cumulative distribution function

$$G\left(x_1^1, ..., x_N^J\right) = \exp\left(- \sum_{n=1}^{N} \left(\sum_{j=1}^{J} \exp\left(- \frac{x_n^j}{\nu} \right) \right)^{\frac{\nu}{\kappa}} \right). \tag{7}$$

Preference draws are i.i.d. across households. As we will see later, the parameter ν governs the elasticity of within-commuting zone industry choices to wage differences, while the parameter κ governs the elasticity of commuting zone choices to wage differences.

Production Each commuting zone n produces a non-tradable final consumption good, assembled as a Cobb-Douglas aggregate from the final goods of J industries. We have

$$Q_n = \prod_{j=1}^{J} \left(Q_n^j \right)^{\alpha^j}, \tag{8}$$

where Q_n is the output of the final consumption good in commuting zone n, Q_n^j is the output of the final good of industry j in commuting zone n, and α^j stands for the spending share of industry j. Spending shares are non-negative and hold $\sum_{j=1}^{J} \alpha^j = 1$.

Industry final goods are also non-tradable, and assembled from a continuum $[0, 1]$ of differentiated goods with a CES production function:

$$Q_n^j = \left(\int_0^1 \left(q_n^j(\omega) \right)^{\frac{\varepsilon-1}{\varepsilon}} d\omega \right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{9}$$

where $q_n^j(\omega)$ stands for the use of differentiated good ω of industry j in commuting zone n, and the positive parameter ε is the elasticity of substitution between differentiated goods. Each differentiated good ω of industry j can be produced in any commuting zone n, with a production technology using labor and intermediate inputs. The production function is

$$y_n^j(\omega) = \tilde{z}_n^j(\omega) \left(\ell_n^j(\omega) \right)^{\varphi^j} \prod_{s=1}^{J} \left(m_n^{sj}(\omega) \right)^{\varphi^{sj}}, \text{ where } \tilde{z}_n^j(\omega) \equiv E_n^{-\psi} \lambda_n^j z_n^j(\omega). \tag{10}$$

In this expression, $\ell_n^j(\omega)$ stands for the number of workers hired by firms producing differentiated good ω of industry j in commuting zone n, while $m_n^{sj}(\omega)$ stands for the amount of the final good of industry s they use as intermediate input. The input share parameters φ^j and $\left(\varphi^{sj}\right)_{s=1}^{J}$ are non-negative and hold $\varphi^j + \sum_{s=1}^{J} \varphi^{sj} = 1$. Note that these input shares are industry-specific, but do not vary across commuting zones.

The productivity of firms producing differentiated good ω of industry j in commuting zone n, $\tilde{z}_n^j(\omega)$, depends on three components:

1. **An idiosyncratic productivity** $z_n^j(\omega)$**.** Idiosyncratic productivities are drawn from a Fréchet distribution with parameters (ζ_n^j, θ^j). ζ_n^j governs the average productivity of industry j in commuting zone n, while θ^j captures its productivity dispersion.

2. **An emission abatement** $1 - \lambda_n^j$**.** We assume that firms are required by the government to devote a fraction $1 - \lambda_n^j$ of their output to emission abatement. Hence, only the remaining fraction λ_n^j is available for sale.

3. **An emission externality** $E_n^{-\psi}$**.** This externality is common across all firms in a commuting zone and depends on commuting zone emissions, denoted by E_n. We assume $\psi \geq 0$, so that emissions have a negative effect on productivity.[17] Emissions are an endogenous outcome, but as firms are atomistic, they take E_n as given.

[17] Empirical studies have shown that air pollution increases sick leave and decreases cognitive ability (Dechezleprêtre *et al.*, 2019, Leroutier and Ollivier, 2023). Note that our assumption of a commuting

Differentiated goods are tradable, and producers can export them to other commuting zones subject to iceberg trade costs. Precisely, in order to deliver one unit of a differentiated good of industry j from commuting zone i to commuting zone n, firms need to ship d_{ni}^{j} units. Differentiated goods producers hire workers on a competitive labor market that is commuting zone-industry specific, and all firms sell their goods under perfect competition.

Finally, fine particle emissions for the producer of differentiated good ω in industry j of commuting zone n hold

$$\frac{e_n^j(\omega)}{y_n^j(\omega)} = \sigma_n^j \cdot \left(\lambda_n^j\right)^{\beta^j}, \tag{11}$$

where $e_n^j(\omega)$ stands for the emissions generated by production. This formulation is in line with the literature (see e.g. Shapiro and Walker, 2018). Emissions scale linearly in output. Emission intensity (i.e., emissions per unit of output) is the same for all firms in a commuting zone-industry, and depends on two factors: technology and abatement. The positive parameter σ_n^j, capturing technology, is the emission intensity that would prevail without any abatement. More abatement (i.e., a lower value of λ_n^j) lowers the emission intensity, with the abatement elasticity β^j governing the strength of this effect.

We assume that the abatement parameters λ_n^j are exogenously set by a government. As equation (11) shows, this is isomorphic to the government mandating an emission intensity for each commuting zone and industry.[18] This is effectively what the EPA does when it mandates firms to use technologies with the "lowest achievable emission rates".

Trade balance and government spending Without additional assumptions, our model implies that in every commuting zone n, the revenue of each final goods producer equals the total spending of local households and differentiated goods firms on their good. In real-world data, these accounting equations do not hold: for instance, some commuting zones have trade deficits and spend more than what is warranted by their income.[19]

To match the data, we introduce government spending. We assume that in each commuting zone-industry pair (n, j), the government either buys up or sells some units of the final industry good. These purchases or sales are proportional to the total revenue of the final good producer, denoted by X_n^j. Thus, private spending on the final good equals $\left(1 - \tau_n^j\right) X_n^j$, with government purchases accounting for a fraction τ_n^j of industry revenue

zone-level externality is appropriate for the pollutants we consider here, as their effect is mostly local. This assumption would be less appropriate for modeling emissions of greenhouse gases such as CO_2 or methane.

[18] Appendix C.3 shows that an alternative model with pollution taxes leads to the same conclusions.

[19] Our model also assumes that consumption and intermediate input shares are identical across commuting zones. This is a simplifying assumption, as there is no commuting-zone-level data to discipline these shares.

if $\tau_n^j > 0$, or sales accounting for a fraction τ_n^j of industry revenue if $\tau_n^j < 0$. For every industry j, we assume that the net impact of these purchases or sales across commuting zones is zero, such that

$$\sum_{n=1}^{N} \tau_n^j X_n^j = 0. \tag{12}$$

That is, government purchases in some commuting zones are financed by sales in others.

4.2 Equilibrium conditions in relative changes

To study the effect of fine particle regulations in our model, we will compare a pre-reform equilibrium to a post-reform equilibrium, assuming that the only parameters that change between equilibria are the abatement requirements λ_n^j. To compare equilibria, it is convenient to solve the model in relative changes. That is, for any variable v, we solve for $\widehat{v} \equiv \frac{v'}{v}$, where v stands for the value of the variable in the pre-reform equilibrium, and v' for its value in the post-reform equilibrium. We only state the main results here, and provide further derivations in Appendix C.1.

Households We denote by H_n^j the mass of households in commuting zone n and industry j, and by H_n the total mass of households in commuting zone n (holding $H_n \equiv \sum_{j=1}^{J} H_n^j$). Changes in the distribution of households across industries within a commuting zone hold

$$\frac{\widehat{H}_n^j}{\widehat{H}_n} = \frac{\left(\widehat{w}_n^j\right)^{\frac{(1+\zeta)(1-\chi)}{\nu(1+\zeta\chi)}}}{\sum_{s=1}^{J} \frac{H_n^s}{H_n} \left(\widehat{w}_n^s\right)^{\frac{(1+\zeta)(1-\chi)}{\nu(1+\zeta\chi)}}}. \tag{13}$$

Thus, industries experiencing an increase in wages relative to the commuting zone average attract a greater share of the commuting zone's population. The scale of this change depends on the parameters ζ and χ, which determine the elasticity of utility to wages, and on the parameter ν, the inverse elasticity of industry choice with respect to utility.

Changes in the total mass of households in a commuting zone hold

$$\widehat{H}_n = \frac{\left(\sum_{j=1}^{J} \frac{H_n^j}{H_n} \left(\frac{\widehat{w}_n^j}{\widehat{P}_n}\right)^{\frac{(1+\zeta)(1-\chi)}{\nu(1+\zeta\chi)}}\right)^{\frac{\nu}{\kappa}}}{\sum_{i=1}^{N} H_i \left(\sum_{j=1}^{J} \frac{H_i^j}{H_i} \left(\frac{\widehat{w}_i^j}{\widehat{P}_i}\right)^{\frac{(1+\zeta)(1-\chi)}{\nu(1+\zeta\chi)}}\right)^{\frac{\nu}{\kappa}}}. \tag{14}$$

Commuting zones which see an increase in real wages relative to the average experience an increase in population. The size of these changes depends again on the utility parameters ζ and χ and on the inverse industry switching elasticity ν. However, it also depends on the inverse migration elasticity κ: all else equal, a higher value for this parameter (i.e., a lower elasticity) implies smaller changes in population.

All households within a commuting zone-industry pair choose the same labor supply. Denoting total labor supply in commuting zone n and industry j by L_n^j, we get

$$\widehat{L}_n^j = \widehat{H}_n^j \left(\frac{\widehat{w}_n^j}{\widehat{P}_n} \right)^{\frac{\zeta(1-\chi)}{1+\zeta\chi}}. \tag{15}$$

Labor supply is the model's equivalent to employment in the data. Equation (15) shows that changes in labor supply are driven both by an extensive margin (a change in the mass of households in the commuting zone-industry) and an intensive margin (a change in the labor supplied by each household, in response to the change in the real wage).[20] The elasticity of labor supply to the real wage is increasing in the Frisch elasticity ζ.

Production As shown in equation (10), externalities and abatement have a symmetric effect across all firms in a commuting zone-industry. Thus, firm productivity $\tilde{z}_n^j$ follows a Fréchet distribution, with parameters (T_n^j, θ^j).[21] Changes in abatement shift its level parameter, which holds

$$\widehat{T}_n^j = \left(\widehat{E}_n\right)^{-\psi\theta^j} \left(\widehat{\lambda}_n^j\right)^{\theta^j}. \tag{16}$$

Thus, the average productivity in a commuting zone-industry decreases with abatement (which uses output) and with commuting zone emissions (due to the emission externality).

Changes in productivity trigger changes in trade patterns. Denoting by π_{ni}^j the share of spending of the final goods producer of industry j in commuting zone n that is spent on differentiated goods from commuting zone i, we have

$$\widehat{\pi}_{ni}^j = \frac{\widehat{T}_i^j \left(\widehat{u}_i^j\right)^{-\theta^j}}{\sum_{k=1}^{N} \pi_{nk}^j \widehat{T}_k^j \left(\widehat{u}_k^j\right)^{-\theta^j}}. \tag{17}$$

[20] The baseline model of Caliendo *et al.* (2019) assumes that households supply labor inelastically, but can move to a home production industry. Our model instead allows for the elasticity of employment to the real wage to be different from the elasticity of location choices with respect to the real wage.

[21] The level parameter of this Fréchet distribution is $T_n^j = \xi_n^j (E_n)^{-\psi\theta^j} \left(\lambda_n^j\right)^{\theta^j}$.

In this expression, u_i^j stands for the unit cost of inputs (labor and intermediates) for differentiated goods producers in industry j and commuting zone i. In any industry j, the final producer of commuting zone n spends more on differentiated goods from commuting zone i if there is an decrease in the relative cost of that commuting zone with respect to all others. Costs depend negatively on productivity T_i^j and positively on input costs u_i^j.

Changes in the unit cost of inputs are a weighted average of changes in wages and changes in the price of intermediate inputs:

$$\widehat{u}_n^j = \left(\widehat{w}_n^j\right)^{\varphi^j} \prod_{s=1}^{J} \left(\widehat{P}_n^s\right)^{\varphi^{sj}}. \tag{18}$$

Changes in the price of the final good of industry j in commuting zone n are given by

$$\widehat{P}_n^j = \left(\sum_{i=1}^{N} \pi_{ni}^j \widehat{T}_i^j \left(\widehat{u}_i^j\right)^{-\theta^j}\right)^{-\frac{1}{\theta^j}}. \tag{19}$$

This change is a spending-share weighted average of the change in production costs in all origin commuting zones from which the final goods producer of commuting zone n buys its differentiated goods. In turn, aggregate price indices hold

$$\widehat{P}_n = \prod_{j=1}^{J} \left(\widehat{P}_n^j\right)^{\alpha^j}. \tag{20}$$

Finally, recall that we denote by X_n^j the revenue of the final good producer of industry j in commuting zone n.[22] This revenue (plus any revenue from government sales of the final good) must be equal to total spending on the final good (including government spending). This implies

$$\left(1 - \tau_n^j\right) X_n^j = \alpha^j \underbrace{\left(\sum_{s=1}^{J} w_n^s L_n^s\right)}_{X_{C,n}^j} + \sum_{s=1}^{J} \varphi^{js} \underbrace{\left(\sum_{i=1}^{N} \pi_{in}^s X_i^s\right)}_{X_{II,n}^{js}}. \tag{21}$$

Private spending on each good (the left-hand side of equation (21)) is final producer revenue minus net government purchases. This is equal to the sum of consumption spending $X_{C,n}^j$ (the first term on the right-hand side) and spending on good j as an intermediate input (the second term on the right-hand side). Consumption spending is a fixed fraction α^j

[22]Perfect competition implies that this revenue is equal to the total cost of the final good producer (i.e., its total spending on differentiated goods).

of commuting zone income. Intermediate input spending on good j comes from differentiated goods producers of any industry s in commuting zone n, and is a fraction φ^{js} of the gross output of these differentiated goods producers. Their gross output, in turn, is the sum of their sales across all destinations.[23] Expressing this equation in relative changes, we get

$$\begin{aligned}\widehat{X}_n^j &= \frac{X_{C,n}^j}{\left(1-\tau_n^j\right)X_n^j}\widehat{X}_{C,n}^j + \sum_{s=1}^{J}\frac{X_{II,n}^{js}}{\left(1-\tau_n^j\right)X_n^j}\widehat{X}_{II,n}^{js} \\ &= \frac{X_{C,n}^j}{\left(1-\tau_n^j\right)X_n^j}\sum_{s=1}^{J}\frac{w_n^s L_n^s}{\sum_{b=1}^{J} w_n^b L_n^b}\widehat{w}_n^s\widehat{L}_n^s + \sum_{s=1}^{J}\frac{X_{II,n}^{js}}{\left(1-\tau_n^j\right)X_n^j}\left(\sum_{i=1}^{N}\frac{\pi_{in}^s X_i^s}{\sum_{k=1}^{N}\pi_{kn}^s X_k^s}\widehat{\pi}_{in}^s\widehat{X}_i^s\right)\end{aligned} \tag{22}$$

Changes in spending are a weighted average of changes in consumption and intermediate input spending. The change in consumption spending is equal to the change in commuting zone income (which is a weighted average of changes in the wage bill for every industry). In turn, changes in intermediate input spending by any industry s are equal to changes in the gross output of this industry. The change in gross output of industry s in commuting zone n is a weighted average of changes in the spending on industry s in each destination commuting zone i. The weights on each destination commuting zone i are given by its initial share in the gross output of industry s in commuting zone n.

Finally, changes in the wage bill in each commuting zone-industry pair (n, j) are also equal to changes in the gross output of that commuting zone-industry pair, so that

$$\widehat{w}_n^j\widehat{L}_n^j = \sum_{i=1}^{N}\widehat{\pi}_{in}^j\widehat{X}_i^j\frac{\pi_{in}^j X_i^j}{\sum_{k=1}^{N}\pi_{kn}^j X_k^j}. \tag{23}$$

Emissions We denote by E_n^j the total emissions of all differentiated goods producers in the commuting zone-industry pair (n, j). The change in these emissions is given by

$$\widehat{E}_n^j = \left(\widehat{\lambda}_n^j\right)^{\beta^j}\sum_{i=1}^{N}\frac{d_{in}^j\pi_{in}^j X_i^j/P_i^j}{\sum_{k=1}^{N} d_{kn}^j\pi_{kn}^j X_k^j/P_k^j}\frac{\widehat{\pi}_{in}^j\widehat{X}_i^j}{\widehat{P}_i^j}. \tag{24}$$

Industry-level emissions change because of changes in abatement (which changes emission intensities) and changes in scale. These changes in scale are a weighted average of changes in sold quantities for all destination commuting zones that buy goods from

[23] Thus, the gross output of differentiated goods producers holds $\mathrm{GO}_n^j = \sum_{i=1}^N \pi_{in}^j X_i^j$. Note that gross output of differentiated goods producers GO_n^j is not equal to the spending on the final good, X_n^j.

commuting zone-industry pair (n, j).[24] Aggregate emission changes are a weighted average of industry-level changes:

$$\widehat{E}_n = \sum_{j=1}^{J} \frac{E_n^j}{E_n} \widehat{E}_n^j. \tag{25}$$

Summing up, equations (13) to (25) define a non-linear system of equations which pins down our model's solution in relative changes. Appendix C.2 describes the numerical algorithm that we use to compute this solution. The next section instead turns to discussing how we calibrate the model to assess the aggregate impact of the EPA's fine particle regulations.

5 Calibration

Throughout, we consider the year 1999 as corresponding to the pre-reform equilibrium, and the year 2016 as corresponding to the post-reform equilibrium. Recall that the only difference between these two equilibria is a change in abatement $\widehat{\lambda}_n^j$.

As the equations in Section 4.2 indicate, solving for the equilibrium in relative changes requires knowing three sets of numbers: some characteristics of the pre-reform equilibrium (e.g., the initial distribution of households and fine particle emissions), the changes in abatement $\widehat{\lambda}_n^j$, and values for the model parameters. In this section, we describe how we calibrate these three elements.

5.1 Characteristics of the pre-reform equilibrium

Equations (13) to (25) feature several pre-reform equilibrium outcomes, such as the initial distribution of households and fine particle emissions across commuting zones and industries, or the distribution of industry trade flows. Appendix C.4 contains a full list of the pre-reform outcomes needed to solve the model, and describes in detail how we calibrate them. Besides the data introduced in Section 2, the calibration also requires data on gross output and input-output linkages (from the Bureau of Economic Analysis) and on trade flows within the United States (from the Census Bureau's Commodity Flow Survey).

Three important points are worth noting here. First, for computational reasons, we limit the number of commuting zones and industries in our quantitative analysis. We focus on the 130 commuting zones with the highest employment in 1999, aggregating all others into a "Rest of the US" commuting zone (so that $N = 131$). We also aggregate

[24] Accordingly, the weights in equation (24) are analogous to the ones in equation (23). The only difference is that the shares in the equation for emissions are computed with physical units (instead of nominal sales) and refer to gross production, including iceberg trade costs.

all non-manufacturing industries (with the exception of utilities and mining) to a generic non-manufacturing industry. Finally, we aggregate a few manufacturing industries for which the BEA does not provide disaggregated output data. These choices imply $J = 21$.

Second, our calibration of initial trade flows (summarized by the trade shares π^j_{ni}), uses the Commodity Flow Survey. We assume that utilities and our generic non-manufacturing industry, for which there is no data in this survey, are not traded (implying $\pi^j_{nn} = 1$).

Third, as Appendix C.4 shows, pre-reform data directly pins down values for four series of model parameters: the consumption spending shares α^j (pinned down by initial consumption data), the production function parameters φ^j and φ^{sj} (pinned down by input-output data), and the government spending parameters τ^j_n (pinned down by the implied trade imbalances for every commuting zone-industry pair).

5.2 Changes in abatement costs

To calibrate changes in abatement costs, we rely on the structure imposed by our model. As all firms within a commuting zone-industry pair have the same emission intensity, the industry-level emission intensity holds

$$\frac{E^j_n}{Y^j_n} = \sigma^j_n \cdot \left(\lambda^j_n\right)^{\beta^j}, \tag{26}$$

where Y^j_n is the total physical output of differentiated goods producers in industry j and commuting zone n (i.e., $Y^j_n \equiv \int_0^1 y^j_n(\omega)$). Thus, our model implies a log-linear relationship between changes in industry-level emission intensity and changes in abatement:

$$\ln \widehat{\left(\frac{E^j_n}{Y^j_n}\right)} = \beta^j \ln\left(\widehat{\lambda}^j_n\right). \tag{27}$$

To map this relationship to the data, we impose two assumptions, in line with the institutional setup and our empirical analysis in Section 3. First, we assume that the reform only changed abatement for polluting industries in non-attainment commuting zones (and had no effect on abatement in clean industries and/or attainment commuting zones). Second, we assume that for polluting industries in non-attainment commuting zones, the change in emission intensity triggered by the reform holds

$$\ln \widehat{\left(\frac{E^j_n}{Y^j_n}\right)} = \gamma_E \cdot S^{\mathrm{NA}}_n, \tag{28}$$

where γ_E is a parameter. That is, the change in emission intensity is a linear function of the commuting zone's non-attainment status, captured (as in our empirical analysis) by the percentage of the population living in non-attainment counties, S_n^{NA}.[25]

The parameter γ_E in equation (28) captures the change in the emission intensity of polluting industries in non-attainment commuting zones triggered by the reform. In our empirical analysis, we estimated this change in Column (1) of Table 3, which contains the results for the exact equivalent of equation (28).[26] Scaling up this estimate (which refers to annual changes) for a 13-year-long post-reform period, we obtain $\gamma_E = 0.078 \cdot 13 = 1.014$. Thus, for a commuting zone entirely composed of non-attainment counties ($S_n^{\mathrm{NA}} = 1$), the emission intensity of polluting industries decreases by 101.4 log points, or 64%.

This estimate helps to pin down changes in abatement costs. Indeed, equation (27) shows that, conditional on assuming values for the abatement elasticities β^j, the estimated change in emission intensity directly yields an estimate for changes in abatement $\widehat{\lambda}_n^j$. We discuss our calibration of the abatement elasticities in the next section.

5.3 Elasticity parameters

Externally and internally calibrated parameters Given our previous choices, we are left with seven series of elasticity parameters to be calibrated: the trade elasticities θ^j, the income elasticity of labor supply χ, the Frisch elasticity of labor supply ζ, the inverse migration elasticity κ, the inverse industry switching elasticity ν, the emission externality ψ, and the abatement elasticities β^j.

We calibrate several of these parameters externally. We follow Costinot and Rodríguez-Clare (2014) to set trade elasticities to $\theta^j = 5$, and Rodríguez-Clare *et al.* (2020) to set the inverse industry switching elasticity to $\nu = 0.55$. As in Acemoglu and Restrepo (2020), we set the income elasticity of labor supply to $\chi = 0.02$. Finally, we also externally calibrate the Frisch elasticity of labor supply ζ. For this parameter, there is a wide range of estimates in the literature (see e.g. Chetty *et al.*, 2011). Our baseline calibration considers an elasticity of $\zeta = 2$, in line with commonly used values in the macroeconomic literature. However, we will also consider an alternative calibration with a lower elasticity of $\zeta = 1$.

The remaining elasticities are calibrated internally. We assume that abatement elasticities

[25] For the 130 largest commuting zones, we directly observe S_n^{NA} in the data. We assume that the "Rest of the US" commuting zone is in attainment, so that $S_{131}^{\mathrm{NA}} = 0$.

[26] In the data, we have estimated the change of emission intensity in non-attainment relative to attainment commuting zones. However, in our model, the relative change in emission intensity is equal to the absolute one, as the emission intensity of polluting industries in attainment commuting zones is unaffected by the reform. Hence, our analysis is internally consistent: there are no general equilibrium spillovers for emission intensity in our model (although there are of course such spillovers for emissions and employment).

do not vary across industries, so that $\beta^j = \beta$.[27] Then, we calibrate β, the emission externality ψ and the inverse migration elasticity κ to match our empirical results for the effects of the reform on employment and population growth across commuting zones.

Regarding employment growth, we use the data generated by our model to estimate the regression

$$\ln \widehat{L_n^j} = \gamma_{L,1}^{\text{Model}} \cdot S_n^{\text{NA}} + \gamma_{L,2}^{\text{Model}} \cdot \left(S_n^{\text{NA}} \cdot \text{Emit}_{1999}^j \right) + \alpha^j + \epsilon_n^j. \tag{29}$$

This regression is equivalent to our empirical specification in column (2) of Table 1, with $\gamma_{L,1}^{\text{Model}}$ capturing the overall difference in employment growth between non-attainment and attainment commuting zones, and $\gamma_{L,2}^{\text{Model}}$ the additional difference in employment growth for polluting industries.[28] Hence, we aim for the model to reproduce our empirical results, which imply that for a 13-year post-reform period, $\gamma_{L,1}^{\text{Data}} = 0$ and $\gamma_{L,2}^{\text{Data}} = -0.0143 \cdot 13 = 0.1859$. Note that we set the coefficient for the overall difference in employment growth between non-attainment and attainment commuting zones to zero, as the empirical estimate was not statistically different from (and close to) zero. Appendix D.3 considers a robustness check targeting the actual point estimate.

Regarding population growth, we use the model data to estimate

$$\ln \widehat{H_n} = \gamma_{\text{Pop}}^{\text{Model}} \cdot S_n^{\text{NA}} + \epsilon_n. \tag{30}$$

This regression is equivalent to our empirical specification in column (1) of Table 4, and we aim for the model to reproduce the empirical result $\gamma_{\text{Pop}}^{\text{Data}} = 0$. That is, there should be on average no difference between population growth in non-attainment and attainment commuting zones after the reform.

Summing up, we set the three internally calibrated elasticity parameters such that they match the three regression coefficients described above.[29] The next section discusses in detail how the regression coefficients identify the parameters.

Identification of internally calibrated parameters As the regression coefficients are a non-linear function of model parameters, identification is not obvious a priori. However, as we show in this section, each regression coefficient is mostly determined by one model parameter, and there are clear economic intuitions for these relationships.

Consider first the coefficient $\gamma_{L,2}$ in the employment regression, which captures the

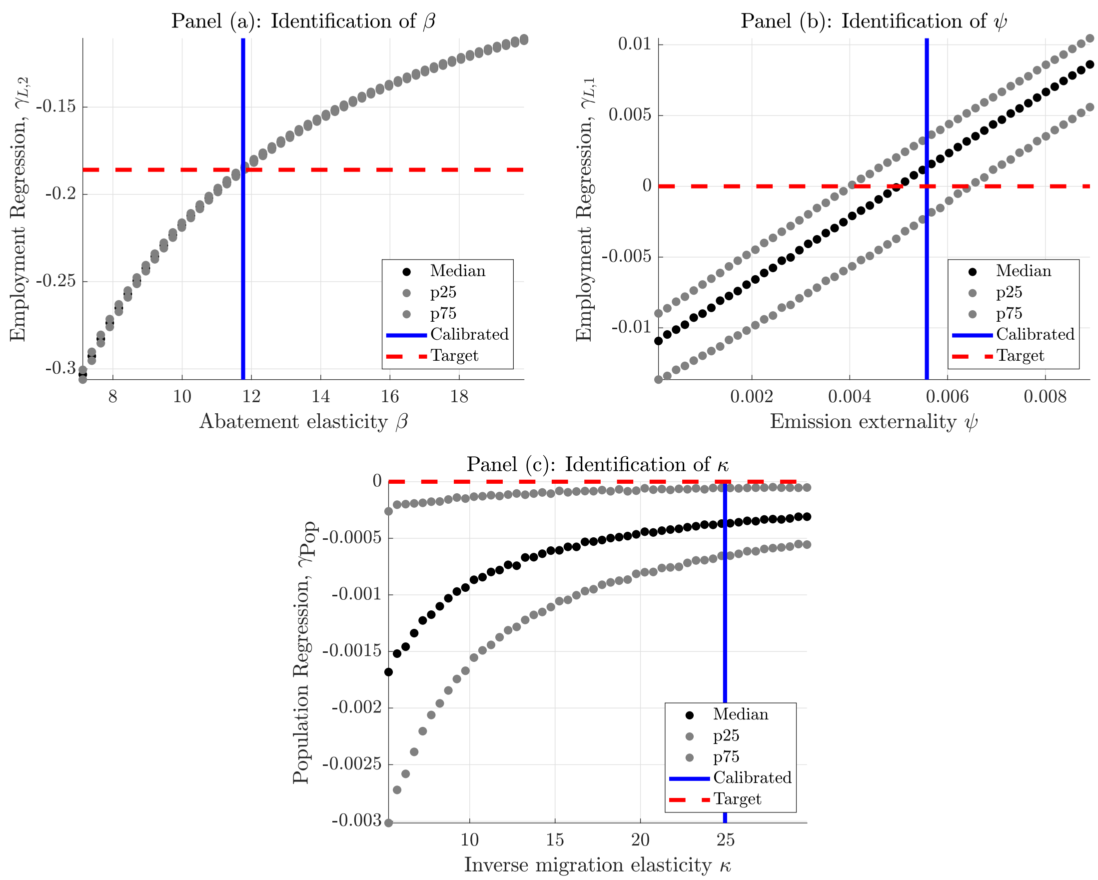
[27] Appendix D.2 relaxes this assumption, by using elasticity estimates from Shapiro and Walker (2018).

[28] As in the data, we estimate model regressions by WLS, weighting observations by initial employment.

[29] Formally, we choose (β, ψ, κ) to minimize the distance function $\sum_{m=1}^{3} \left| \frac{\exp\left(\text{Moment}_m^{\text{Model}}\right) - \exp\left(\text{Moment}_m^{\text{Data}}\right)}{\exp\left(\text{Moment}_m^{\text{Data}}\right)} \right|$. We apply the exponential transformation because some moments are equal to zero.

change in the relative employment of polluting industries in non-attainment commuting zones. In our model, this mostly depends on the abatement elasticity β, which governs how emission intensity reductions map into productivity. With a low elasticity, lower emissions imply a big reduction in productivity, and our model accordingly predicts a large drop in the relative employment of polluting industries. On the other hand, with a high elasticity, reducing emission intensity has only a small effect on productivity, and there is hardly any difference between employment changes in polluting and clean industries.

Figure 5: Identification of internally calibrated parameters



Notes: This figure shows the relationship between the targeted moments and our internally calibrated parameters. To construct the figure, we draw a large sample of parameter vectors. In each panel, we choose one parameter (shown on the x-axis), and split the sample into 50 bins according to the values taken by this parameter. We then compute for each bin the median value as well as the 25th and 75th percentile for a chosen moment (shown on the y-axis). The red horizontal line indicates the value of the targeted moment in the data, and the blue vertical line the calibrated value of the parameter.

Panel (a) of Figure 5 formalizes this intuition, by plotting the value for the coefficient $\gamma_{2,L}$ obtained in our model against different values of the abatement elasticity β. To construct this figure, we randomly draw a large number of values for the three internally calibrated parameters and split these draws into 50 bins, based on their value for β. Thus, each bin fixes β within a narrow interval, but allows for random variation in the two other parameters. The black dots in the figure indicate the median value of the coefficient $\gamma_{2,L}$ for each bin, and the grey dots indicate the 25th and 75th percentiles. The figure confirms that our target identifies the abatement elasticity: there is a clear positive relation between $\gamma_{2,L}$ and β, validating the economic intuition laid out above. Moreover, the tight interquartile range shows that $\gamma_{2,L}$ is virtually insensitive to the values of the other parameters.

Next, we turn to the other coefficient in the employment regressions, $\gamma_{L,1}$. This coefficient captures the overall difference in employment growth between attainment and non-attainment commuting zones. Both in the model and in the data, its value is mostly pinned down by clean industries (which account for over 95% of employment). The relative employment growth of clean industries crucially depends on the emission externality ψ. The reform reduces emissions in non-attainment commuting zones. With a strong externality (a high value of ψ), this leads to a large productivity increase for clean industries in non-attainment commuting zones, raising their real wages and employment relative to their peers in attainment commuting zones. On the other hand, with a weak externality (a low value of ψ), clean industries perform worse in non-attainment commuting zones: their productivity hardly increases, and the shock to polluting industries implies falling real wages and rising input prices.[30] Panel (b) of Figure 5 corroborates this intuition.

Finally, our empirical results for the difference in population growth between commuting zones identify the inverse migration elasticity κ, as shown in panel (c) of Figure 5. Higher values for κ imply that household location choices respond less to changes in wages, and therefore, differences in population growth across commuting zones are more muted.

Calibrated parameter values and model fit Table 5 summarizes the calibrated values for the elasticity parameters, as well as the model's fit. The model successfully matches our empirical estimates, fitting all three regression coefficients virtually perfectly.

With our abatement elasticity of $\beta = 11.8$, the 64% reduction in emission intensity implied by the reform lowers the productivity of polluting industries by around 8.2%. Our estimate is close to Shapiro and Walker (2018), who find abatement elasticities around 15 for the most polluting manufacturing industries (Appendix D.2 considers a robustness check using their estimates). Our inverse migration elasticity κ is higher than the one estimated by Rodríguez-Clare *et al.* (2020), who find $\kappa = 12.3$. However, both values have similar

[30] Without trade costs, changes in real wages and prices would have a uniform effect across all commuting zones. However, in the presence of trade costs, there is a home bias: local goods are over-represented in the local consumption and intermediate input baskets, and local industries are therefore hit harder.

implications, namely a very small migration response. Finally, our externality parameter ψ implies that a 10% reduction in emissions triggers a small 0.06% increase in productivity.

Table 5: Calibrated values for the elasticity parameters

Parameter	Value	Interpretation	Target/Source	Model	Data
ψ	0.0056	Agg. emission externality	$\gamma_{L,1}$	-0.0001	0
κ	24.95	Inverse migration elasticity	γ_{Pop}	-0.0003	0
β	11.76	Abatement elasticity	$\gamma_{L,2}$	-0.1861	-0.1859
ζ	2	Frisch elast. of lab. supply			
χ	0.02	Income elast. of lab. supply	AR (2020)		
θ^j	5	Trade elasticity	CRC (2014)		
ν	0.55	Industry switching elast.	RCUV (2020)		

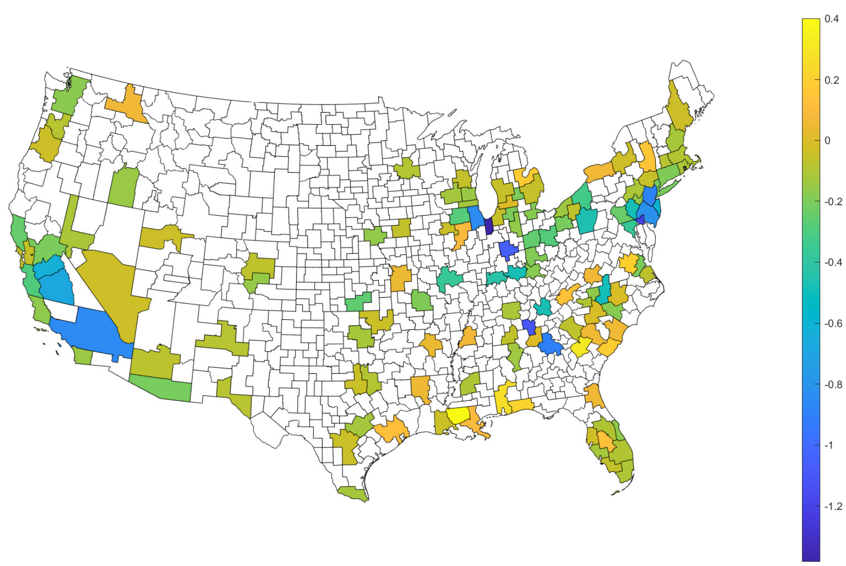
Notes: Calibration targets are described in the text. AR (2020) stands for Acemoglu and Restrepo (2020), CRC (2014) for Costinot and Rodríguez-Clare (2014) and RCUV (2020) for Rodríguez-Clare *et al.* (2020).

6 Aggregate and local effects of the reform

6.1 Employment effects

We are now ready to consider the effects of the reform in our calibrated model. Figure 6 provides an overview of the reform's local implications, showing changes in employment for all commuting zones included in our analysis.

Figure 6: The impact of the reform on commuting zone employment



Notes: This map shows employment changes between the pre and post-reform equilibrium (expressed in percent) for the 130 largest commuting zones. All others are aggregated into a "rest of the US" commuting zone.

For most commuting zones, the reform reduced employment. While this decline was on average larger for non-attainment commuting zones, there is a wide range of outcomes. For non-attainment commuting zones, outcomes range from a 1.38% decline in employment in Gary (IN) to no change in Rome (GA). For attainment commuting zones, the range goes from a 0.32% decline in Erie (PA) to a 0.40% increase in Baton Rouge (LA).

Table 6 summarizes our most important results. It shows outcomes for the United States as a whole, for an aggregate of non-attainment and attainment commuting zones, and for the fifteen largest commuting zones. Confirming the impression from Figure 6, we find that the reform had an economic cost in terms of lost jobs, lowering employment in both polluting and clean industries.

Table 6: Employment effects of the reform

	NA Status	**Employment**	**Emp.: Polluting**	**Emp.: Clean**
United States		-0.25%	-0.50%	-0.24%
Non-attainment CZs	0.76	-0.54%	-10.51%	-0.23%
Attainment CZs	0.00	-0.08%	4.13%	-0.25%
Los Angeles	0.95	-0.85%	-13.43%	-0.57%
New York	0.99	-0.21%	-10.42%	-0.08%
Chicago	1.00	-0.84%	-14.41%	-0.42%
Newark	0.94	-0.89%	-10.29%	-0.50%
Boston	0.00	-0.09%	4.62%	-0.19%
Philadelphia	0.90	-0.81%	-11.25%	-0.49%
Detroit	0.88	-0.06%	-11.44%	0.18%
San Francisco	0.00	-0.05%	4.42%	-0.14%
Houston	0.00	0.13%	2.95%	0.03%
Atlanta	0.98	-0.90%	-13.94%	-0.62%
Dallas	0.00	-0.09%	3.52%	-0.16%
Minneapolis	0.00	-0.09%	3.79%	-0.18%
Seattle	0.00	-0.17%	3.16%	-0.24%
Bridgeport	0.50	-0.19%	-3.90%	-0.08%
Phoenix	0.00	-0.07%	3.28%	-0.15%

Notes: This table shows the predictions of our calibrated model for the change in employment between the pre and post-reform equilibrium."Non-attainment CZs" stands for an aggregate of all commuting zones in which at least one county is non-attainment. "Attainment CZs" is an aggregate of all other commuting zones. "NA Status" stands for the non-attainment status of a commuting zone, given by S_n^{NA}, the share of a commuting zone's population living in non-attainment counties. For aggregate categories, this is a simple average across commuting zones. "Emp.: Polluting" refers to total employment in polluting industries, and "Emp.: Clean" to total employment in clean industries.

Consider first the case of polluting industries. For these, higher abatement lowers firm productivity in non-attainment commuting zones. As a result, polluting employment in non-attainment commuting zones falls by 10.51%. However, the reform also has a positive spillover effect on polluting industries in attainment commuting zones, which increase employment by 4.13%. This dampens the aggregate loss of polluting employment, which adds up to 0.50% of the pre-reform level (approximately 19'000 jobs).

To get a sense of the importance of general equilibrium effects, it is useful to compare this number to a naive extrapolation from our empirical results. In the data and in the model, the reform lowers the relative employment of polluting industries in non-attainment commuting zones by 0.1859 log points, or 16.6%. Moreover, non-attainment commuting zones account for roughly 30% of pre-reform polluting employment. Hence, if we were to ignore general equilibrium effects (i.e., assuming that employment in clean industries and attainment commuting zones does not change), we would compute an aggregate polluting employment loss of $16.6\% \cdot 30\% = 4.98\%$ (or 189'000 jobs).[31] This exceeds our model's prediction by an order of magnitude. Thus, ignoring general equilibrium effects would substantially overstate employment losses in polluting industries.

Next, consider clean industries. While these are not directly affected by the reform, our model suggests that they experience negative spillovers: both in non-attainment and attainment commuting zones, clean employment falls by about 0.24% (corresponding to $248'000$ jobs). Thus, even though there is no difference in clean employment growth between commuting zones, clean employment declines. This decline is due to general equilibrium spillovers, and would have been missed by a naive extrapolation from our empirical results.

Taking stock, our model implies that the reform led to a loss of approximately $267'000$ jobs, widely spread across industries. Instead, ignoring general equilibrium effects would have implied a loss of $189'000$ jobs, entirely concentrated in polluting industries. Thus, general equilibrium spillovers are crucial to understand the impact of the reform. However, what is their exact nature, and what determines their quantitative importance? In the next section, we delve deeper into these questions.

6.2 Understanding general equilibrium spillovers

The reform has a direct effect on polluting industries in non-attainment commuting zones: higher abatement lowers firm productivity. Our estimate for the fall in emission

[31] This approximate computation disregards the fact that commuting zones have different percentages of their population in non-attainment. However, computing total polluting employment losses more exactly as $\sum_j \sum_n \exp\left(\gamma_{L,2}\right) S_n^{\mathrm{NA}} \mathrm{Emit}_{1999}^j L_n^j$ delivers virtually the same result, a 5% reduction.

intensity and our calibrated value for the abatement elasticity β (disciplined by our estimate for relative employment changes in polluting industries) pin down the size of this shock. All else equal, the shock increases polluting firms' prices, lowers their workers' wages, and lowers commuting zone-level emissions. The original shock then sets off several general equilibrium spillover effects, which can be grouped into six categories:

1. **Trade.** In tradable polluting industries, the shock leads to a reallocation of demand: firms in non-attainment commuting zones become less competitive and lose market shares to firms in attainment commuting zones. Hence, this channel tends to increase polluting employment in attainment commuting zones.

2. **Industry switching.** Lower wages in polluting industries provide an incentive for workers to switch to clean industries within the same commuting zone. This channel thus tends to increase clean employment in non-attainment commuting zones.

3. **Migration.** Lower wages in polluting industries also provide an incentive for workers to move to other commuting zones. However, our low migration elasticity (disciplined by our empirical finding on population growth) implies that this channel is quantitatively small.

4. **Labor supply.** All else equal, higher prices for polluting goods imply lower real wages for all households that consume these goods. With our calibrated utility function, labor supply is decreasing in the real wage, so that this channel lowers employment. As most polluting goods are tradable, this affects households in both attainment and non-attainment commuting zones. However, due to a home bias in consumption, non-attainment commuting zones are more strongly affected.

5. **Input-Output linkages.** Polluting industries are typically upstream industries (most clearly so in the case of utilities). Thus, an increase in their prices increases costs for their customers, and this cost shock sets off a similar series of spillovers as the initial abatement shock. This channel is stronger for more downstream industries and – due to a home bias in intermediate input use – in non-attainment commuting zones.

6. **Emission externality.** Lower emissions in non-attainment commuting zones increase their firms' productivity. This dampens the negative productivity shock for polluting industries, and gives a positive productivity shock to clean industries. The latter shock then triggers the spillovers described in points 1 to 5 above, but with the opposite sign: affected clean firms gain market shares and attract workers. All else equal, this increases clean employment in non-attainment commuting zones.

These spillovers drive our model's employment predictions. For polluting industries, we found that an increase in employment in attainment commuting zones dampens overall job losses (see Table 6). Our discussion above shows that the only spillovers that can explain this increase are trade and migration. However, migration is quantitatively negligible. Thus, trade is the key factor: the reform reshuffles trade flows, reallocates polluting production, and some lost jobs in non-attainment commuting zones are compensated by new jobs created in attainment commuting zones. In line with this, Figure A.2 in the Appendix shows that attainment commuting zones with a greater pre-reform presence of tradable polluting industries experienced greater gains in polluting employment.

Understanding our findings for clean employment is more involved. Table 7 summarizes the key forces at play, as a function of the two productivity shocks in non-attainment commuting zones: a direct negative productivity shock to polluting industries, and an indirect positive productivity shock to clean industries (triggered by the emission externality).

Table 7: Spillovers for employment in clean industries

Non-attainment commuting zones Productivity shocks	**Non-attainment commuting zones Change in clean emp.**	**Attainment commuting zones Change in clean emp.**
↑ clean ind. productivity		
Trade	↑	↓
Industry switching	↑	↓
Labor supply, IO linkages	↑↑	↑
↓ poll. ind. productivity		
Industry switching	↑	↓
Labor supply, IO linkages	↓↓	↓

Table 7 shows that most spillovers lower clean employment in attainment commuting zones. Indeed, their clean firms lose market shares to more productive competitors in non-attainment commuting zones, and workers to expanding polluting industries. Furthermore, higher prices for polluting goods depress labor supply and increase input costs. Except for migration (which is quantitatively negligible, and therefore omitted in the table), the only force that could increase clean employment in attainment commuting zones is the fall in the price of clean goods produced in non-attainment commuting zones, which stimulates labor supply and lowers input costs everywhere. However, due to the home bias, this force is stronger in non-attainment commuting zones. Thus, if this force were large, we should observe that clean employment grew more in non-attainment commuting zones. However, our empirical results indicate that there was no difference in clean employment growth between commuting zones. As a result, the positive productivity shock to clean industries must be small relative to the negative productivity shock to polluting industries, and this in turn implies that clean employment in attainment commuting zones must fall. Hence, general equilibrium effects exacerbate job losses in clean industries.[32]

This discussion shows that both the magnitude of the original abatement shock and its spillover effects are disciplined by our calibration (and hence by our empirical estimates). Section 6.4 assesses the sensitivity of our results to different estimates and calibration choices. First, however, the next section discusses results for outcomes besides employment.

6.3 Emissions, GDP per worker and population

Table 8 lists our model's predictions for the impact of the reform on emissions, GDP per worker and population.

Table 8: Changes in other economic outcomes after the reform

	NA Status	**Emissions**	**GDP/Worker**	**Population**
United States		-11.1%	-0.13%	-0.00%
Non-attainment CZs	0.76	-50.6%	-0.49%	-0.02%
Attainment CZs	0.00	1.1%	0.07%	0.01%
Los Angeles	0.95	-38.4%	-0.61%	-0.03%
New York	0.99	-55.6%	-0.25%	0.00%
Chicago	1.00	-44.2%	-0.75%	-0.03%
Newark	0.94	-53.8%	-0.89%	-0.04%
Boston	0.00	0.2%	0.08%	0.01%
Philadelphia	0.90	-44.3%	-0.62%	-0.03%
Detroit	0.88	-52.4%	-0.21%	0.01%
San Francisco	0.00	-0.1%	0.01%	0.01%
Houston	0.00	0.7%	0.15%	0.02%
Atlanta	0.98	-37.4%	-0.57%	-0.04%
Dallas	0.00	2.0%	0.01%	0.01%
Minneapolis	0.00	0.4%	0.05%	0.01%
Seattle	0.00	0.6%	-0.06%	0.00%
Bridgeport	0.50	-36.1%	-0.21%	0.00%
Phoenix	0.00	1.0%	0.03%	0.01%

Notes: This table lists predictions for changes in outcomes between the pre and post-reform equilibrium.

[32]This reasoning echoes the identification discussion in Section 5: to match our empirical finding of equal growth in clean employment across commuting zones, the productivity gains of clean industries in non-attainment commuting zones (disciplined by the emission externality ψ) cannot be too large.

In our empirical analysis, we found that the reform decisively lowered the emission intensity of polluting industries in non-attainment commuting zones. In line with this, our model predicts that the reform triggered a substantial 11.1% reduction in aggregate fine particle emissions (representing one fifth of the total reduction in emissions observed in the data between 2002 and 2017). This reduction is driven by non-attainment commuting zones, which reduced emissions by more than 50%. Spillovers on attainment commuting zones are limited, with their emissions increasing by around 1%.

The table also shows that the reform lowered aggregate GDP per worker by 0.13%.[33] This is due to the negative productivity shock to polluting industries in non-attainment commuting zones, which is not fully compensated by the emission externality. The shock lowers productivity in non-attainment commuting zones, and hence reduces their GDP per worker by 0.49%. In the average attainment commuting zone, on the other hand, GDP per worker slightly increases. Finally, in line with our calibration for the migration elasticity, the distribution of the population across commuting zones hardly changes after the reform.

6.4 Robustness checks

In this section, we examine the sensitivity of our results to different empirical estimates, as well as to our calibration choice for the labor supply elasticity.

The role of calibration targets Our discussion in Section 6.2 shows that the magnitude of general equilibrium effects is directly pinned down by the calibration targets from our empirical analysis. Table 9 further explores this point, by illustrating how our results would change when targeting different (counterfactual) estimation results.

The first row of the table recalls some key results from our baseline calibration. Clean employment declines equally in attainment and non-attainment commuting zones, and overall employment falls by 0.25%. This loss exceeds a "naive" estimate (inferred from our regressions and ignoring all general equilibrium effects) by 38%.

In the second row, we target a 1 log point decline in the relative overall employment of non-attainment commuting zones after the reform. All other targets and externally calibrated parameters are unchanged. In particular, we still target no changes in population between commuting zones, which shuts down migration. In this calibration, the overall decline in employment increases to 0.56%. Indeed, to match the decline in employment

[33]At the commuting zone level, we compute changes in GDP per worker as changes in the real wage bill per worker. For aggregate outcomes, we compute a weighted average of these changes, with weights given by each commuting zone's initial share in the aggregate wage bill.

Table 9: The role of calibration targets

	Emp.	**Emp. (naive)**	**Clean Emp., NA**	**Clean Emp., A**
Baseline ($\gamma_{L,1} = \gamma_{\text{Pop}} = 0$)	-0.25%	-0.18%	-0.23%	-0.25%
$\gamma_{L,1} = -0.01;\ \gamma_{\text{Pop}} = 0$	-0.56%	-0.49%	-1.07%	-0.24%
$\gamma_{L,1} = -0.01;\ \gamma_{\text{Pop}} = -0.005$	-0.49%	-0.50%	-1.02%	-0.16%
$\gamma_{L,1} = 0.01;\ \gamma_{\text{Pop}} = 0$	-0.02%	0.05%	0.42%	-0.26%

Notes: Each line corresponds to a different set of calibration targets. In each case, we re-calibrate internal model parameters to match the new targets, and keep all other targets and external parameters unchanged.

in non-attainment commuting zones, our calibration reduces the emission externality.[34] This implies less of a dampening of productivity losses from higher abatement, but also weaker general equilibrium spillovers. As a result, the actual employment loss is now closer to a naive extrapolation from our regressions (obtained by assuming that attainment commuting zones are unaffected by the reform), exceeding it by only 14%. In the third row, we also allow for a small decrease in the population of non-attainment commuting zones. This increases the migration elasticity (κ falls from 25.0 in the baseline to 5.5). Aggregate employment losses are dampened, as migration can generate changes in relative employment without changes in aggregate employment.

Finally, in the fourth row, we target an increase in the relative employment of non-attainment commuting zones. This increases our estimate for the emission externality, and essentially eliminates the aggregate job loss: clean employment now expands sufficiently in non-attainment commuting zones to make up for job losses elsewhere.

The Frisch elasticity of labor supply In our baseline calibration, we set the Frisch elasticity to 2, a common value in the macroeconomic literature. However, there is considerable uncertainty about the appropriate value of this parameter (see e.g. Chetty *et al.*, 2011). As our baseline value is relatively high with respect to microeconometric estimates, we now analyse how our results change with a lower elasticity of $\zeta = 1$. All other external parameter values and calibration targets are unchanged.

In this alternative calibration, we obtain a lower value for the abatement elasticity β, which now equals 10.0 (rather than 11.8 in the baseline). This implies that the reduction in

[34]This is fully in line with the identification intuitions shown in Figure 5. Precisely, our estimate for ψ falls from 0.0056 in the baseline to 0.0014. The estimates for the parameters β and κ, on the other hand, are hardly affected: they are equal to 11.7 and 26.4, versus 11.8 and 25.0 in the baseline.

emission intensity had a higher productivity cost. Indeed, given the lower Frisch elasticity, employment reacts less to any given shock. Therefore, the calibration needs to increase the shock size to keep matching our regression results for the reaction of employment in polluting industries. The emission externality ψ is somewhat smaller than in the baseline (0.0047 against 0.0056), and the inverse migration elasticity κ is virtually the same (27.2 against 25.0).

Table 10: Main model results for a lower Frisch elasticity of labor supply

	NA	**Employment**	**Emp.: Polluting**	**Emp.: Clean**	**GDP/Worker**
United States		-0.21%	-0.53%	-0.20%	-0.22%
Non-attainment CZs	0.76	-0.51%	-10.54%	-0.19%	-0.73%
Attainment CZs	0.00	-0.05%	4.09%	-0.21%	0.06%
Los Angeles	0.95	-0.65%	-13.42%	-0.37%	-0.84%
New York	0.99	-0.35%	-10.61%	-0.22%	-0.50%
Chicago	1.00	-0.67%	-14.29%	-0.25%	-1.01%
Newark	0.94	-0.76%	-10.22%	-0.36%	-1.22%
Boston	0.00	-0.06%	4.61%	-0.16%	0.08%
Philadelphia	0.90	-0.66%	-11.16%	-0.34%	-0.87%
Detroit	0.88	-0.23%	-11.66%	0.01%	-0.42%
San Francisco	0.00	-0.03%	4.39%	-0.12%	0.00%
Houston	0.00	0.08%	2.94%	-0.01%	0.16%
Atlanta	0.98	-0.69%	-13.72%	-0.42%	-0.81%
Dallas	0.00	-0.05%	3.60%	-0.12%	0.01%
Minneapolis	0.00	-0.06%	3.83%	-0.15%	0.04%
Seattle	0.00	-0.10%	3.28%	-0.17%	-0.08%
Bridgeport	0.50	-0.24%	-4.00%	-0.13%	-0.36%
Phoenix	0.00	-0.04%	3.34%	-0.12%	0.03%

Notes: This table lists our key results for a calibration that assumes a Frisch elasticity of labor supply of $\zeta = 1$. All other parameters and calibration targets are the same as in the baseline.

Table 10 summarizes some key outcomes for the alternative calibration. First, it is worth noting that the lower labor supply elasticity does not affect our results for polluting industries: the decline in polluting employment in non-attainment commuting zones and the increase in polluting employment in attainment commuting zones are virtually the same as in our baseline. However, spillovers for clean industries are weaker. As a result, overall clean employment falls only by 0.20% (instead of 0.24% in the baseline). This is a direct consequence of the lower labor supply elasticity: the weaker reaction of employment to the shock outweighs the larger size of the shock. Therefore, the overall employment loss now amounts to 228’000 jobs, as opposed to 267’000 in the baseline.[35]

Summing up, this analysis suggests that our estimates for polluting industries are very robust to different assumptions about the labor supply elasticity. However, the magnitude of general equilibrium spillovers for clean industries depends on this elasticity to some extent (even though their sign does not).

7 Conclusions

In this paper, we have developed a quantitative model, disciplined by extensive empirical evidence, to estimate the effect of air pollution regulations introduced by the EPA in the early 2000s. We found that the regulations substantially lowered fine particle emissions, but also led to a loss of between 228’000 and 267’000 jobs.

The main implication from our analysis is that general equilibrium spillovers are crucial to assess the aggregate impact of environmental policy. While our exact results are specific to the air pollution regulations studied in this paper, our approach can easily be extended to study similar policies in other time periods or countries. In particular, the set of spillover forces highlighted in our discussion is likely to be at play for other location-specific environmental policies. Thus, in many circumstances, ignoring spillover effects of environmental policies could lead policymakers to substantially overestimate employment losses in polluting industries, and to miss employment losses in clean industries. This matters for the cost-benefit analysis of these policies, but also for their political economy implications. For instance, if (as our analysis suggests) job losses from environmental policy are more widely diffused through industries and space than previously thought, their impact is both less salient to the affected workers and more difficult to compensate.

[35] It is also worth noting that GDP per worker declines slightly more in this calibration. This is a direct consequence of the fact that we now need a greater productivity shock to match our employment regression results: as productivity declines more, GDP per worker also takes a bigger hit.

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A Data Appendix (for online publication only)

A.1 Commuting zone attainment status

The EPA reports county attainment status for different pollutants in its Green Book.[36] For counties exceeding the NAAQS thresholds, the EPA further distinguishes between "wholly non-attainment" and "partially non-attainment", where the latter designation refers to counties in which some areas are in attainment of the standards. We map counties to commuting zones using the correspondence table created by Chetty *et al.* (2014). We then measure a commuting zone's status by computing the share of its population living in counties that are wholly or partially non-attainment. County population is measured in 2003 (the pre-reform year), and taken from Census data described in Appendix A.3.

Table A.1: Average commuting zone characteristics by attainment status

	Attainment	Non-attainment
Number of CZs	679	62
Employment	99.6	702.1
Population	264.4	1739.1
Fine particle emissions	732.4	4290.5
Fine particle emissions per worker	0.016	0.031
Employment share of polluting industries	0.047	0.054
Urban comm. zone dummy	0.395	0.919
Labor force participation	0.616	0.622
Foreign born share	0.040	0.059
Income growth, 2000-2010	-0.001	-0.006
Growth in imports from China	1.174	1.189

Notes: This table lists simple averages for different characteristics across attainment and non-attainment commuting zones. Employment and population are stated in thousands, while fine particle emissions are stated in tons. The first five variables are taken from our baseline data, and computed as averages over the period 2001-2003. The last five variables are from Chetty *et al.* (2014), described in greater detail below.

Table A.1 compares some characteristics of attainment and non-attainment commuting zones (where the latter are defined as commuting zones that have at least one non-attainment county). It shows that non-attainment commuting zones are larger, more urban, and have higher emissions of fine particles per worker.

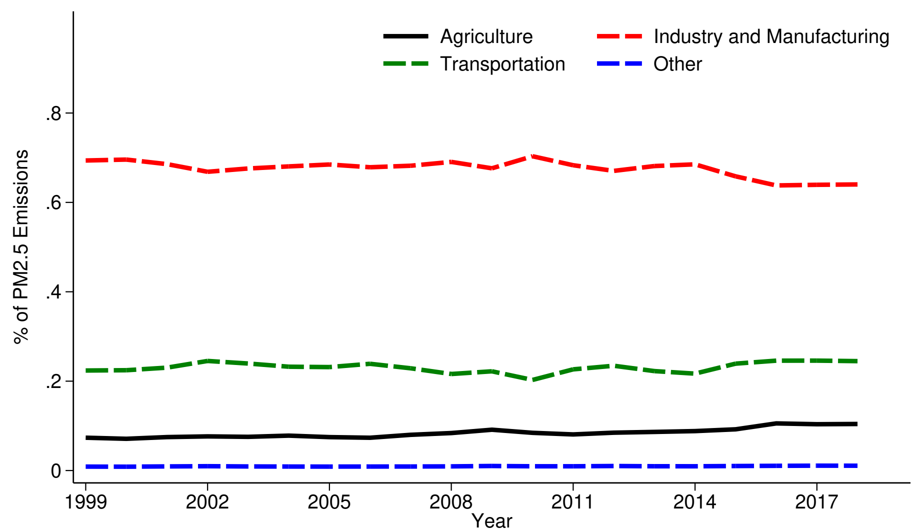
[36]Data from the Green Book can be downloaded at `https://www.epa.gov/green-book/green-book-data-download`.

A.2 Air pollution emissions

Our data for emissions comes from the EPA's National Emissions Inventory (NEI).[37] The NEI contains information on emissions at the facility level.[38] We use its data for primary fine particle ($PM_{2.5}$) emissions.

Until 2001, the NEI uses the Standard Industrial Classification (SIC), and from 2002 onward, it uses different vintages of the North American Industry Classification System (NAICS). In order to ensure comparability across time, we convert all data into 3-digit NAICS 2012 codes, using the concordance tables of Eckert *et al.* (2020). These are the same concordance tables that are used for our employment data. Finally, we aggregate emissions data to the commuting zone-industry level, mapping counties into commuting zones with the correspondence table of Chetty *et al.* (2014).

Figure A.1: Sources of fine particle emissions in the United States



Notes: This figure illustrates the main sources of fine particle emissions in the United States. Data is taken from the European Commission's Emissions Database for Global Atmospheric Research (EDGAR).

While the NEI data captures only emissions from industrial production, it is useful to confront this with emissions from other sources. Using data from EDGAR, Figure A.1

[37]Data from the NEI can be downloaded at https://www.epa.gov/air-emissions-inventories/national-emissions-inventory-nei.

[38]Emissions for most facilities are not directly observed by the EPA, but computed based on emission factors. An emission factor is a representative value that indicates the amount of a pollutant released into the atmosphere per unit of some measured activity (e.g., kilograms of fine particles emitted per megagram of coal burned). Emissions are estimated as $E = A \cdot EF \cdot (1 - ER/100)$, where E indicates pollution emissions, A the activity rate, EF the emission factor, and ER the overall emission reduction efficiency. The factors vary depending on locality and source and are adjusted over time.

decomposes total fine particle emissions in the United States between 1999 and 2018. This shows that industrial production is the largest source of emissions, accounting for 69% of the total in 1999. The remainder of emissions is made up by transportation (e.g., personal car use) and agriculture. However, industrial emissions have also declined somewhat faster than emissions in other sectors, so that their share has fallen to 64% in 2018.

A.3 Employment, population and commuting zone characteristics

We use data on employment at the county-industry level from the US Census Bureau's County Business Patterns (CBP), as adjusted by Eckert *et al.* (2020).[39] These authors have done extensive work to impute missing values, correct noise infusions, and convert the data into consistent industry codes (using the 2012 NAICS classification). We aggregate this dataset to the commuting zone-industry level. As for all other data, we map counties into commuting zones by using the correspondence table of Chetty *et al.* (2014), and define industries at the 3-digit NAICS level.

We obtain data on county population by year from the US Census Bureau.[40] Again, we aggregate this data to the commuting zone level. Finally, we use data on commuting zone characteristics compiled by Chetty *et al.* (2014). We use five variables: a dummy for urban commuting zones (i.e., commuting zones that intersect with a Metropolitan Statistical Area), the percentage growth in imports from China between 1990 and 2000 (originally computed by Autor *et al.*, 2013), the labor force participation rate, the fraction of foreign born inhabitants, and commuting zone income growth between 2000 and 2010 (all computed from Census data).

A.4 Other data for the calibration

This section describes data that is only used for the calibration of our model. Appendix C.4 discusses how this data is used.

Trade To measure trade flows between commuting zones, we rely on the Census Bureau's Commodity Flow Survey (CFS) for the year 1997.[41] This database contains the value of shipments of different goods between states and Metropolitan Statistical Areas (MSAs).

[39] The data can be downloaded at `http://www.fpeckert.me/cbp/`.

[40] Data can be downloaded at `https://www.census.gov/data/datasets/time-series/demo/popest/intercensal-2000-2010-counties.html` and `https://www.census.gov/data/datasets/time-series/demo/popest/2010s-counties-total.html`.

[41] CFS data can be downloaded at `https://www.census.gov/programs-surveys/cfs.html`.

It uses the Standard Classification of Transported Goods (SCTG), which we convert into NAICS 3-digit codes, and covers manufacturing industries and mining.

This dataset does not have information on trade at the commuting zone level. Thus, we construct shipments between commuting zones by splitting up shipments between states. To do so, we start by splitting up origin states into origin commuting zones, using employment weights in 1997.[42] That is, if commuting zone n represents 15% of total employment of state S in industry j, we assume that commuting zone n also represents 15% of total exports of state S in industry j to any destination state. Then, we split up destination states into destination commuting zones, using population weights in 1997.[43] That is, if 20% of the population of state S lives in commuting zone n, we assume that 20% of shipments to state S in any industry go to commuting zone n.

However, to adjust for home bias, we follow a different rule for splitting up intra-state destinations. Here, we apply a correction factor, computed using shipment data for MSAs. Our correction factor is the ratio between the percentage of within-state shipments that stay in the origin MSA, and the percentage of the state's population living in an MSA.[44] We compute this statistic at the industry-MSA level, and take a simple average over MSAs to obtain an industry-specific correction factor. We then multiply the within-commuting-zone shipments obtained in our imputation with this correction factor (and reduce shipments to other within-state commuting zones, in order to keep total shipments unchanged).

Gross output, consumption, and intermediate inputs To discipline intermediate input shares and consumption shares, we rely on an input-output use table from the Bureau of Economic Analysis (BEA) for the year 1999.[45] This data contains information on the use of gross output at the industry-level, distinguishing between consumption, intermediate inputs, inventories, investment and government purchases. We adjust the raw data by removing inventories, government purchases, investment and international trade, all of which do not feature in our model.[46] Precisely, we compute an adjusted measure of gross output by subtracting the change in inventories and exports from the BEA measure of gross output. We also lump private investment and government purchases into consumption. Finally, we subtract imports from consumption and intermediate input use, distributing total imports according to the pre-adjustment levels of these variables.

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[42] Employment data comes from the same dataset described in section A.3.

[43] Again, the population data comes from the same dataset described in section A.3.

[44] Assume, for example, that 20% of steel shipments from Pittsburgh to Pennsylvania stay in Pittsburgh, and that Pittsburgh represents 5% of Pennsylvania's population. Then, the correction factor in this case is $20/5 = 4$.

[45] The data is at `https://www.bea.gov/industry/input-output-accounts-data`.

[46] Our model's government purchases are just a helpful shortcut to adjust for trade deficits.

B Additional empirical results (for online publication only)

B.1 Summary statistics

Table A.2 shows summary statistics for the variables included in our commuting zone-industry regressions, while Table A.3 shows summary statistics for variables included in our commuting zone regressions.

Table A.2: Summary statistics (commuting zone-industry level)

	N	Mean	St. Dev.	Median	p10	p90
$\ln L^j_{n,t} - \ln L^j_{n,t-1}$	851592	0.0040	0.2391	0.0045	-0.2466	0.2509
Emit^j_{1999}	892144	0.0682	0.2521	0	0	0
S^{NA}_n	892144	0.0771	0.2353	0	0	0.2311
$\frac{1}{3}\left(\ln E^j_{n,t} - \ln E^j_{n,t-3}\right)$	7458	-0.0483	0.3152	-0.0296	-0.4897	0.3364
$\frac{1}{3}\left(\ln \tilde{E}^j_{n,t} - \ln \tilde{E}^j_{n,t-3}\right)$	7410	-0.0358	0.3215	-0.0262	-0.4840	0.3630
Labor force participation	892144	0.6202	0.0567	0.6235	0.5477	0.6906
Growth in imports from China	878636	1.2724	1.7384	0.8121	0.1514	2.6859
Foreign born share	892144	0.0428	0.0504	0.0264	0.0089	0.0973
Urban comm. zone dummy	892144	0.5477	0.4977	1.0000	0.0000	1.0000
Income growth, 2000-2010	892144	-0.0027	0.0093	-0.0032	-0.0128	0.0080

Notes: This table lists summary statistics for variables used in the regressions in Sections 3.1 and 3.2. Summary statistics for changes in emissions and changes in emission intensity are only shown for the sample of polluting industries. $\tilde{E} \equiv E/L$ stands for emission intensity. Growth in imports from China is measured over the period 1990-2000, while the foreign born share and the labor force participation rate are measured in 2000.

Table A.3: Summary statistics (commuting zone level)

	N	Mean	St. Dev.	Median	p10	p90
$\ln \text{Pop}_{n,t} - \ln \text{Pop}_{n,t-1}$	15225	0.0038	0.0173	0.0032	-0.0090	0.0176
$\ln L_{n,t} - \ln L_{n,t-1}$	15225	0.0057	0.0486	0.0083	-0.0413	0.0482
$\frac{1}{3}\left(\ln E_{n,t} - \ln E_{n,t-3}\right)$	3816	-0.0500	0.2528	-0.0329	-0.3642	0.2016
Labor force participation	16586	0.6154	0.0593	0.6193	0.5392	0.6894
Growth in imports from China	16183	1.1796	1.8001	0.7440	0.0607	2.6655
Foreign born share	16586	0.0395	0.0479	0.0236	0.0083	0.0902
Urban comm. zone dummy	16586	0.4297	0.4950	0.0000	0.0000	1.0000
Income growth, 2000-2010	16586	-0.0016	0.0122	-0.0024	-0.0128	0.0117

Notes: This table lists summary statistics for variables used in the regressions in Sections 3.3 and B.3.

B.2 Additional regression results at the commuting zone-industry level

Tables A.4 to A.7 contain further robustness checks for the results shown in the main text. Table A.4 shows how our results change when we consider the effects of the reform to start in 2005 rather than in 2004, and when we use a continuous measure for polluting industries. In both cases, results are similar to our baseline findings in Table 1. Table A.5 considers a further robustness check on the definition of polluting industries. In the baseline, industries were considered polluting if they represented more than 4% of national emissions in 1999. Here, we increase this threshold to 5% (which reduces the number of polluting industries from 6 to 4, i.e., to the same sample of polluting industries considered in our robustness checks for emissions in Tables 2 and 3 in the main text). Results are again similar to our baseline, although somewhat smaller in magnitude.

Tables A.6 and A.7, in turn, revisit our results for emissions and emission intensity. In our baseline analysis, we attributed changes between 2002 and 2005 to the post-reform period. However (irrespective of whether we consider the reform to take effect in January 2004 or in January 2005) this period is partly pre-reform and partly post-reform. Thus, we show here that our results do not change when we omit this period from our regressions.

Table A.4: Employment growth regressions - robustness

	(1)	(2)	(3)	(4)	(5)	(6)
$S_n^{\text{NA}} \cdot \text{Emit}_{1999}^j \cdot \mathbb{1}_t^{\text{Post}}$	-0.009**	-0.010**	-0.010**	-0.023	-0.027*	-0.028*
	(0.004)	(0.004)	(0.004)	(0.016)	(0.015)	(0.015)
$S_n^{\text{NA}} \cdot \mathbb{1}_t^{\text{Post}}$		-0.003	0.000		-0.002	0.003
		(0.003)	(0.004)		(0.002)	(0.004)
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
CZ-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
CZ-year FE	Yes	No	No	Yes	No	No
N	851571	851592	838698	851571	851592	838698
R^2	0.298	0.263	0.264	0.298	0.263	0.264

Notes: This table illustrates two further robustness checks on our baseline results shown in the first three columns of Table 1. In columns (1)-(3), we assume that the pre-reform year is 2004 rather than 2003 (i.e., the dummy variable $\mathbb{1}_t^{\text{Post}}$ is equal to 1 starting in 2005). In columns (4)-(6), we replace the dummy variable Emit_{1999}^j with a continuous variable, equal to the share of industry j in total fine particle emissions in 1999. The dependent variable is winsorized to be between -0.69 and 0.69 log points. Observations are weighted by commuting zone-industry employment in 1995. Standard errors clustered by state in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.5: Employment growth regressions - further robustness

	(1)	(2)	(3)
$S_n^{\text{NA}} \cdot \text{Emit}_{1999}^{j} \cdot \mathbb{1}_t^{\text{Post}}$	-0.006**	-0.007**	-0.008**
	(0.003)	(0.003)	(0.003)
$S_n^{\text{NA}} \cdot \mathbb{1}_t^{\text{Post}}$		-0.002	0.003
		(0.002)	(0.004)
N	851571	851592	838698
R^2	0.298	0.263	0.264

Notes: This table illustrates a further robustness check on our baseline results shown in the first three columns of Table 1. Here, we consider an industry as polluting if it accounts for more than 5% of national emissions in 1999 (in the baseline, this threshold was at 4%). The dependent variable is winsorized to be between -0.69 and 0.69 log points. Observations are weighted by commuting zone-industry employment in 1995. Standard errors clustered by state in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.6: Emission regressions - omitting 2002-2005

	(1)	(2)	(3)	(4)	(5)	(6)
$S_n^{\text{NA}} \cdot \mathbb{1}_t^{\text{Post}}$	-0.076**	-0.077**	-0.085**	-0.085**	-0.055*	-0.059**
	(0.036)	(0.032)	(0.038)	(0.034)	(0.032)	(0.028)
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
CZ-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6215	6185	4375	4345	6215	6185
R^2	0.242	0.246	0.234	0.237	0.242	0.246

Notes: This table reproduces Table 2, omitting data for 2002-2005. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.7: Emission intensity regressions - omitting 2002-2005

	(1)	(2)	(3)	(4)	(5)	(6)
$S_n^{\text{NA}} \cdot \mathbb{1}_t^{\text{Post}}$	-0.080*	-0.083**	-0.090**	-0.093**	-0.061	-0.066**
	(0.041)	(0.036)	(0.043)	(0.039)	(0.037)	(0.032)
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
CZ-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6169	6139	4340	4310	6169	6139
R^2	0.229	0.232	0.224	0.226	0.229	0.232

Notes: This table reproduces Table 3, omitting data for 2002-2005. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

B.3 Employment and emissions at the commuting zone level

In the main text, we use a difference-in-difference regression, specified in equation (5), to compare population growth between commuting zones after the reform. Tables A.8 and A.9 show our results for the same specification when using the growth rate of commuting zone employment or commuting zone emissions as the dependent variable.

The results are in line with our baseline analysis for employment and emissions at the commuting zone-industry level. There is no significant difference in overall employment growth across commuting zones after the reform. However, fine particle emissions fall substantially more in non-attainment commuting zones.

Table A.8: Changes in commuting zone employment

	(1)	(2)	(3)	(4)
$S_n^{\text{NA}} \cdot \mathbb{1}_t^{\text{Post}}$	-0.001	0.004	-0.001	0.003
	(0.002)	(0.004)	(0.002)	(0.003)
CZ FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	15225	14847	15225	14847
R^2	0.441	0.448	0.441	0.447

Notes: This table is the equivalent of Table 4 in the main text, using commuting zone employment growth instead of commuting zone population growth as the dependent variable.

Table A.9: Changes in commuting zone emissions

	(1)	(2)	(3)	(4)
$S_n^{\text{NA}} \cdot \mathbb{1}_t^{\text{Post}}$	-0.090*	-0.091**	-0.082**	-0.085***
	(0.046)	(0.040)	(0.034)	(0.029)
CZ FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	3816	3774	3816	3774
R^2	0.218	0.223	0.218	0.225

Notes: This table is the equivalent of Table 4 in the main text, using commuting zone emissions growth instead of commuting zone population growth as the dependent variable.

C Model details (for online publication only)

C.1 Equilibrium conditions in levels

In this section, we derive our model's equilibrium conditions in levels.

Labor supply and location choices First, we solve for labor supply choices conditional on location choices. Conditional on locating in commuting zone n and industry j, every household supplies the same amount of labor. This common labor supply choice ℓ_n^j holds the first-order condition

$$\left(\frac{w_n^j}{P_n}\ell_n^j\right)^{-\chi}\frac{w_n^j}{P_n}=\left(\ell_n^j\right)^{\frac{1}{\zeta}}.$$

Therefore, individual labor supply in commuting zone n and industry j is

$$\ell_n^j=\left(\frac{w_n^j}{P_n}\right)^{\frac{\zeta(1-\chi)}{1+\zeta\chi}}.$$

Commuting zone-industry labor supply is

$$L_n^j=H_n^j\left(\frac{w_n^j}{P_n}\right)^{\frac{\zeta(1-\chi)}{1+\zeta\chi}}, \tag{A.1}$$

where, as in the main text, H_n^j stands for the mass of households in commuting zone n and industry j.

Next, we can solve for location choices. Given her labor supply choice, the overall utility for household h from locating in commuting zone n and industry j is

$$\iota_n^j+\eta_n^j\left(h\right)+\ln\left(\frac{1}{1-\chi}-\frac{\zeta}{1+\zeta}\right)+\frac{\left(1+\zeta\right)\left(1-\chi\right)}{1+\zeta\chi}\ln\left(\frac{w_n^j}{P_n}\right).$$

Each household chooses to locate in the commuting zone-industry pair that yields the highest utility for her. Therefore, the probability that she chooses the pair (n,j) is given by

$$H_n^j=\mathbb{P}\left(v_n^j+\eta_n^j\ \geq\ \max_{(i,s)\neq(n,j)}\left(v_i^s+\eta_i^s\right)\right), \tag{A.2}$$

where $v_n^j\equiv\iota_n^j+\frac{(1+\zeta)(1-\chi)}{1+\zeta\chi}\ln\left(\frac{w_n^j}{P_n}\right)$ is constant across workers and $\boldsymbol{\eta}=\left[\eta_1^1,...,\eta_N^J\right]$ is a multivariate random variable with a cumulative distribution function specified in equation (7). This probability also equals the mass of households choosing commuting zone-industry (n, j).

To compute the expression in equation (A.2), note that the law of total probability implies

$$H_n^j = \int_{-\infty}^{+\infty} \mathbb{P}\left(\max_{(i,s)\neq(n,j)} \left(v_i^s + \eta_i^s \right) \le v_n^j + \eta_n^j \mid v_n^j + \eta_n^j = x \right) g_n^j(x)\, dx,$$

where g_n^j is the density of the marginal distribution of $v_n^j + \eta_n^j$. To compute the integral in the above expression, we use the fact that for any continuous random variables X and Y, we have

$$\mathbb{P}\left(Y \le y \,|X = x\right) g_X(x) = \frac{\partial G_{X,Y}}{\partial x}\left(x, y\right),$$

where $G_{X,Y}$ is the joint cumulative distribution function and g_X the density of the marginal distribution of X. Applying this result to our joint cumulative distribution function, we get, after some algebra,

$$H_n^j = \int_{-\infty}^{+\infty} \frac{1}{\kappa} \exp\left(\frac{v_n^j - x}{\nu}\right) \left(\sum_{s=1}^{J} \exp\left(\frac{v_n^s - x}{\nu}\right)\right)^{\frac{\nu}{\kappa}-1} \exp\left(- \sum_{i=1}^{N} \left(\sum_{s=1}^{J} \exp\left(\frac{v_i^s - x}{\nu}\right)\right)^{\frac{\nu}{\kappa}}\right) dx.$$

Simplifying this expression, we obtain

$$H_n^j = \frac{\exp\left(\frac{v_n^j}{\nu}\right)}{\sum_{s=1}^{J} \exp\left(\frac{v_n^s}{\nu}\right)} \left(\sum_{s=1}^{J} \exp\left(\frac{v_n^s}{\nu}\right)\right)^{\frac{\nu}{\kappa}} \int_{-\infty}^{+\infty} \frac{1}{\kappa} \exp\left(-\frac{x}{\kappa}\right) \exp\left(-\Xi \exp\left(-\frac{x}{\kappa}\right)\right) dx.$$

with

$$\Xi = \sum_{i=1}^{N} \left(\sum_{s=1}^{J} \exp\left(\frac{v_i^s}{\nu}\right)\right)^{\frac{\nu}{\kappa}}.$$

Finally, using the change of variables $k = \exp(-\frac{x}{\kappa})$, we get

$$H_n^j = \frac{\left(\sum_{s=1}^{J} \exp\left(\frac{v_n^s}{\nu}\right)\right)^{\frac{\nu}{\kappa}}}{\sum_{i=1}^{N} \left(\sum_{s=1}^{J} \exp\left(\frac{v_i^s}{\nu}\right)\right)^{\frac{\nu}{\kappa}}} \frac{\exp\left(\frac{v_n^j}{\nu}\right)}{\sum_{s=1}^{J} \exp\left(\frac{v_n^s}{\nu}\right)}.$$

Substituting back the expressions for v_n^j, we get that the distribution of households across industries within each commuting zone holds

$$\frac{H_n^j}{H_n} = \frac{\exp\left(\frac{\iota_n^j}{\nu}\right)\left(w_n^j\right)^{\frac{(1+\zeta)(1-\chi)}{\nu(1+\zeta\chi)}}}{\sum_{s=1}^{J}\exp\left(\frac{\iota_n^s}{\nu}\right)\left(w_n^s\right)^{\frac{(1+\zeta)(1-\chi)}{\nu(1+\zeta\chi)}}}. \tag{A.3}$$

Finally, the distribution of households across commuting zones holds

$$H_n = \frac{\left(\sum_{j=1}^{J}\exp\left(\frac{\iota_n^j}{\nu}\right)\left(\frac{w_n^j}{P_n}\right)^{\frac{(1+\zeta)(1-\chi)}{\nu(1+\zeta\chi)}}\right)^{\frac{\nu}{\kappa}}}{\sum_{i=1}^{N}\left(\sum_{j=1}^{J}\exp\left(\frac{\iota_i^j}{\nu}\right)\left(\frac{w_i^j}{P_i}\right)^{\frac{(1+\zeta)(1-\chi)}{\nu(1+\zeta\chi)}}\right)^{\frac{\nu}{\kappa}}}. \tag{A.4}$$

Trade shares and price indices As equation (10) shows, commuting zone emissions and abatement have a symmetric productivity effect across all firms in a commuting zone-industry pair. Therefore, productivity in industry j in commuting zone n is distributed according to a Fréchet distribution with parameters (T_n^j, θ^j), where

$$T_n^j = \xi_n^j \left(E_n\right)^{-\psi\theta^j}\left(\lambda_n^j\right)^{\theta^j}. \tag{A.5}$$

Using this feature, we apply several standard results from Ricardian trade models in the Eaton and Kortum (2002) tradition. π_{ni}^j, the share of spending by the final goods producer of commuting zone n in industry j that is spent on differentiated goods from commuting zone i, holds

$$\pi_{ni}^j = \frac{T_i^j\left(u_i^j d_{ni}^j\right)^{-\theta^j}}{\sum_{k=1}^{N} T_k^j\left(u_k^j d_{nk}^j\right)^{-\theta^j}}. \tag{A.6}$$

Import shares depend on the competitiveness of commuting zone i as a source of imports with respect to all other commuting zones (including the importing commuting zone n). Competitiveness depends on productivity, input costs, and trade costs. Input costs hold

$$u_n^j = \left(\frac{w_n^j}{\varphi^j}\right)^{\varphi^j}\prod_{s=1}^{J}\left(\frac{P_n^j}{\varphi^{sj}}\right)^{\varphi^{sj}}. \tag{A.7}$$

The industry-level price index is

$$P_n^j = A^j \left(\sum_{i=1}^{N} T_i^j \left(u_i^j d_{ni}^j \right)^{-\theta^j} \right)^{-\frac{1}{\theta^j}}, \tag{A.8}$$

where $A^j = \left(\Gamma \left(1 + \frac{1-\varepsilon}{\theta^j} \right) \right)^{\frac{1}{1-\varepsilon}}$, with Γ standing for the gamma function. The aggregate price index in each commuting zone is

$$P_n = \prod_{j=1}^{J} \left(\frac{P_n^j}{\alpha^j} \right)^{\alpha^j}. \tag{A.9}$$

In each commuting zone and industry, the total revenue of the final goods producer (adjusted for government spending) needs to be equal to the total spending by households and differential goods producers. This equality is stated in equation (21) in the main text.

Finally, the labor market in every commuting zone-industry pair must clear. This implies that the wage bill in each commuting zone n and industry j is equal to a fixed fraction of the gross output of differentiated goods producers:

$$w_n^j L_n^j = \varphi^j \sum_{i=1}^{N} \pi_{in}^j X_i^j. \tag{A.10}$$

It is worth noting that these equilibrium conditions imply balanced trade. For each commuting zone n, summing up over industries, we get

$$\sum_{j=1}^{J} \left(1 - \tau_n^j \right) X_n^j = \sum_{j=1}^{J} \left(\sum_{s=1}^{J} \left(\alpha^j \varphi^s + \varphi^{js} \right) \mathrm{GO}_n^s \right) = \sum_{s=1}^{J} \mathrm{GO}_n^s \left(\sum_{j=1}^{J} \alpha^j \varphi^s + \sum_{j=1}^{J} \varphi^{js} \right) = \sum_{s=1}^{J} \mathrm{GO}_n^s \tag{A.11}$$

That is, aggregate private spending in the commuting zone (the left-hand side) is equal to aggregate gross output in the commuting zone (the right-hand side).

Taking emissions as given, equations (A.1) to (A.10) define a system that can be solved for all endogenous variables. To close the model, we therefore need to derive emissions.

Commuting zone-level emissions From equation (11), we get that emissions for a commuting zone-industry pair (n, j) hold

$$E_n^j = \int_0^1 e_n^j(\omega)\, d\omega = \sigma_n^j \left(\lambda_n^j \right)^{\beta^j} \int_0^1 y_n^j(\omega)\, d\omega. \tag{A.12}$$

To evaluate the interval in equation (A.12), we split up the total production of differentiated good ω of industry j in commuting zone n by destination markets, to get

$$\int_0^1 y_n^j(\omega)\, d\omega = \int_0^1 \sum_{i=1}^{N} y_{in}^j(\omega)\, d\omega = \sum_{i=1}^{N} \int_0^1 y_{in}^j(\omega)\, d\omega,$$

where $y_{in}^j(\omega)$ stands for the units of good ω in industry j produced in commuting zone n and shipped to commuting zone i. The second identity follows from Fubini's theorem.

Next, note that

$$\int_0^1 y_{in}^j(\omega)\, d\omega = \int_{\omega\in\Omega_{in}^j} d_{in}^j q_{in}^j(\omega)\, d\omega,$$

where Ω_{in}^j stands for the set of differentiated goods of industry j that are exported from commuting zone n to commuting zone i. Moreover, we have taken into account that the iceberg trade costs create a wedge between production and usage: for every unit being used in commuting zone i, d_{in}^j units have to be produced in commuting zone n.

Demand for each differentiated good ω that is exported from n to i has the standard CES form

$$q_{in}^j(\omega) = \left(\frac{p_{in}^j(\omega)}{P_i^j}\right)^{-\varepsilon} Q_i^j.$$

Replacing this expression into the previous integral, we get

$$\int_0^1 y_{in}^j(\omega)\, d\omega = d_{in}^j \left(P_i^j\right)^{\varepsilon} Q_i^j \int_{\omega\in\Omega_{in}^j} \left(p_{in}^j(\omega)\right)^{-\varepsilon}\, d\omega.$$

To evaluate the above integral, we use two results from Eaton and Kortum (2002). First, the mass of differentiated goods from industry j that commuting zone n exports to commuting zone i is equal to the expenditure share of commuting zone i on goods from commuting zone n in industry j, π_{in}^j. Second, the distribution of prices of differentiated goods from commuting zone n and industry j sold in commuting zone i has the cumulative distribution function

$$G_i^j(p) = 1 - \exp\left(-\Phi_i^j p^{\theta^j}\right),$$

where $\Phi_i^j = \sum_{n=1}^{N} T_n^j \left(u_n^j d_{in}^j\right)^{-\theta^j}$. Remarkably, this distribution does not depend on any characteristics of the commuting zone of origin. Using these two results, we obtain

$$\int_{\omega\in\Omega_{in}^j} \left(p_{in}^j(\omega)\right)^{-\varepsilon}\, d\omega = \pi_{in}^j \int_0^{+\infty} \Phi_i^j \theta^j p^{\theta^j-1-\varepsilon} \exp\left(-\Phi_i^j p^{\theta^j}\right) dp.$$

Using the change of variables $t = \Phi_i^j p^{\theta^j}$, we can compute this integral and obtain

$$\int_{\omega \in \Omega_{in}^j} \left(p_{in}^j(\omega) \right)^{-\varepsilon} d\omega = \pi_{in}^j \left(\Phi_i^j \right)^{\frac{\varepsilon}{\theta^j}} \Gamma \left(1 - \frac{\varepsilon}{\theta^j} \right),$$

where Γ once again denotes the gamma function. Using this result as well as the fact that the industry-level price index holds

$$P_i^j = A^j \left(\Phi_i^j \right)^{-\frac{1}{\theta^j}},$$

we get

$$\int_0^1 y_{in}^j(\omega)\, d\omega = B^j d_{in}^j \pi_{in}^j Q_i^j,$$

where $B^j = \left(A^j\right)^{\varepsilon} \Gamma \left(1 - \frac{\varepsilon}{\theta^j}\right)$ is an industry-specific constant. Thus, industry-level emissions are given by

$$E_n^j = B^j \sigma_n^j \left(\lambda_n^j \right)^{\beta^j} \sum_{i=1}^{N} d_{in}^j \pi_{in}^j Q_i^j. \tag{A.13}$$

Note that by definition, the ideal price index holds $P_i^j Q_i^j = X_i^j$. Therefore, industry-level emissions hold

$$E_n^j = B^j \sigma_n^j \left(\lambda_n^j \right)^{\beta^j} \sum_{i=1}^{N} d_{in}^j \frac{\pi_{in}^j X_i^j}{P_i^j}. \tag{A.14}$$

Equilibrium conditions in relative changes All equilibrium conditions in relative changes can be derived from the equilibrium conditions in levels described in this section through simple algebra.

C.2 Solution algorithm

To solve the model in relative changes, we use the following algorithm.

1. Guess a vector of changes in commuting zone-level emissions, $\widehat{\boldsymbol{E}}_n^{(1)}$.

2. Given this guess, solve for all other endogenous variables.

   (a) Compute changes in productivity $\widehat{T}_n^j$ for every commuting zone-industry pair, using equation (16).

   (b) Guess a value for changes in the nominal wage for every commuting zone-industry, $\widehat{w}_n^{j(1)}$. We normalize $\widehat{w}_N^J = 1$.

i. Solve for changes in the unit cost of inputs, $\widehat{u}_n^j$, and changes in industry-level prices, $\widehat{P}_n^j$, using the non-linear system defined by equations (18) and (19).

ii. Deduce changes in trade shares from equation (17), commuting zone price indices from equation (20), the allocation of households across commuting zones and industries from equations (13) and (14) and changes in employment from equation (15).

iii. Deduce changes in final producer spending from equation (22), which defines a linear system of dimension NJ.

iv. Check whether the labor market clearing conditions in equation (23) hold in every commuting zone-industry pair, up to an error tolerance of 0.2%. When this is the case, proceed to step 3. When this is not the case, update the guess for the change in wages according to

$$\widehat{w}_n^{j(iter+1)} = \widehat{w}_n^{j(iter)} \left(1 - 0.02 \left(\widehat{L}_n^j - \widehat{L}_n^{j(implied)}\right)\right),$$

where $\widehat{L}_n^{j(implied)}$ is the change in employment that would make the labor market clearing condition hold exactly, and return to step 2 (b) i.

3. Deduce the implied change in commuting zone emissions, using equations (24) and (25). If the largest difference between our guess and implied emission changes is lower than 0.01%, the algorithm has converged. Otherwise, update the guess according to

$$\widehat{\boldsymbol{E}}_n^{(iter+1)} = \widehat{\boldsymbol{E}}_n^{\text{implied}}.$$

and return to Step 2 (a).

C.3 Pollution taxes

In this section, we briefly show how a government could use pollution taxes to achieve any desired level of abatement and emission intensity.

We assume that the government imposes a pollution tax τ_n^j for each unit of emissions, and that this tax is proportional to the unit cost $u_n^j/\tilde{z}_n^j(\omega)$ for every producer ω. Firms choose their level of abatement $\lambda_n^j(\omega)$ endogenously, in order to minimize their unit cost. Under these assumptions, the optimal abatement choice solves the problem:

$$\min_{\lambda_n^j(\omega)\in[0,1]} \frac{u_n^j}{\lambda_n^j(\omega) E_n^{-\psi} z_n^j(\omega)} + \tau_n^j \sigma_n^j \left(\lambda_n^j(\omega)\right)^{\beta^j} \frac{u_n^j}{\lambda_n^j(\omega) E_n^{-\psi} z_n^j(\omega)}.$$

This takes into account that the unit cost is now the sum of the cost of producing one unit of saleable output, and the cost of the pollution tax for the emissions caused by this unit of output. When $\beta^j > 1$ (which according to our calibration and Shapiro and Walker (2018) is the empirically relevant case), the solution to this problem holds

$$\lambda_n^j = \min\left(\left(\frac{1}{\tau_n^j \sigma_n^j \left(\beta^j - 1\right)}\right)^{\frac{1}{\beta^j}}, 1\right).$$

Inverting this solution, it is possible to find a level of pollution taxes that rationalizes any chosen level of abatement λ_n^j (and hence any emission intensity).

C.4 Calibration details

This section provides further details for the calibration of the initial equilibrium characteristics and the parameters α^j, τ_n^j, φ^j and φ^{sj}. Table A.10 lists the initial equilibrium characteristics needed to solve the model.

Table A.10: Initial equilibrium characteristics

Variable	Meaning
H_n^j	Share of the total labor force in CZ n and industry j
π_{ni}^j	Share of spending of the final producer of industry j in CZ n on differentiated goods from CZ i
$\frac{\pi_{in}^j X_i^j}{\sum_{k=1}^N \pi_{kn}^j X_k^j}$	Share of spending on differentiated goods from CZ n and industry j accounted for by CZ i
$\frac{d_{in}^j \pi_{in}^j X_i^j / p_i^j}{\sum_{k=1}^N d_{kn}^j \pi_{kn}^j X_k^j / p_k^j}$	Share of physical output of differentiated goods from CZ n and industry j sold to CZ i
$\frac{X_{C,n}^j}{\left(1-\tau_n^j\right) X_n^j}$	Share of consumption spending in total private spending on the final good of industry j in CZ n
$\frac{X_{II,n}^{js}}{\left(1-\tau_n^j\right) X_n^j}$	Share of intermediate input spending by industry s in total private spending on the final good of industry j in CZ n
$\frac{E_n^j}{E_n}$	Share of industry j in CZ n emissions

In order to calibrate these numbers, we use the data described in Appendix A. We approximate labor force shares by data on employment shares, and physical output shares by data on spending shares. Then, our employment data immediately yields the initial distribution of households across commuting zones and industries.[47] Likewise, the emissions

[47]Note that for commuting zone-industry pairs with an employment of zero, we replace the data value with an arbitrarily small number: in our model, there are always at least some households in any commuting

data immediately gives the within commuting zone distribution of emissions.

For the remaining statistics and parameter values, we start by using data from the IO table on the gross output of every industry j and the spending of every industry j on intermediates from any industry s. These data yield the production function parameters. Indeed, as shown in equation (21) of our model,

$$X^{sj}_{II,n} = \varphi^{sj}\mathrm{GO}^{j}_{n}. \tag{A.15}$$

That is, the spending of differentiated goods producers from commuting zone n and industry j on intermediate inputs from industry s is a fixed fraction of their gross output. Summing up across commuting zones, we get

$$\varphi^{sj} = \frac{\sum\limits_{n=1}^{N} X^{sj}_{II,n}}{\sum\limits_{n=1}^{N} \mathrm{GO}^{j}_{n}} = \frac{X^{sj}_{II}}{\mathrm{GO}^{j}}. \tag{A.16}$$

The aggregate data from the IO table gives us the data values of X^{js}_{II} and GO^{s}, and so we can compute the model parameters φ^{js} for every industry pair (j, s). From this, we then immediately deduce the industry labor share as $\varphi^{j} = 1 - \sum\limits_{s=1}^{J} \varphi^{sj}$.

Next, we impute gross output at the commuting zone-industry level, distributing industry gross output by using employment weights. This gives us an equivalent of our model variable $\mathrm{GO}^{j}_{n} = \sum_{i=1}^{N} \pi^{j}_{in} X^{j}_{i}$. Then, we use the trade data from the Commodity Flow Survey to compute, for every origin commuting zone n and every industry j, the percentage of shipments from the origin commuting zone that go to every destination commuting zone i. These numbers are the direct equivalent of the model shares $\frac{\pi^{j}_{in} X^{j}_{i}}{\sum\limits_{k=1}^{N} \pi^{j}_{kn} X^{j}_{k}}$.

Combining the data on the distribution of shipments with the data on gross output, we can now compute the sales of differentiated goods producers from industry j and commuting zone i that go to commuting zone n, X^{j}_{ni} (which is also equal to the spending of the final goods producer from commuting zone n and industry j on differentiated goods from commuting zone i). With this spending data, we can easily compute the trade shares for the calibration:

$$\pi^{j}_{ni} = \frac{X^{j}_{ni}}{\sum\limits_{k=1}^{N} X^{j}_{nk}}$$

zone-industry pair. This does not matter for our results.

Furthermore, this data implies values for the total revenue of the final goods producer of good j in commuting zone n, as

$$X_n^j = \sum_{i=1}^{N} X_{ni}^j.$$

Now, we can sum up equation (21) across commuting zones to get

$$\begin{aligned}
& \sum_{n=1}^{N}\left(1-\tau_n^j\right) X_n^j &=& \sum_{n=1}^{N}\left(\alpha^j\left(\sum_{s=1}^{J} w_n^s L_n^s\right)+\sum_{s=1}^{J}\varphi^{js}\left(\sum_{i=1}^{N}\pi_{in}^s X_i^s\right)\right) \\
\Rightarrow & \sum_{n=1}^{N} X_n^j &=& \alpha^j \sum_{n=1}^{N}\left(\sum_{s=1}^{J} w_n^s L_n^s\right)+\sum_{n=1}^{N}\left(\sum_{s=1}^{J} X_{II,n}^{js}\right) \\
\Rightarrow & \sum_{n=1}^{N}\left(\sum_{i=1}^{N} X_{ni}^j\right) &=& \alpha^j \sum_{n=1}^{N}\left(\sum_{s=1}^{J} w_n^s L_n^s\right)+\sum_{s=1}^{J} X_{II}^{js} \\
\Rightarrow & \sum_{i=1}^{N} \mathrm{GO}_i^j &=& \alpha^j \sum_{n=1}^{N}\left(\sum_{s=1}^{J} w_n^s L_n^s\right)+\sum_{s=1}^{J} X_{II}^{js}
\end{aligned}$$

This implies that consumption shares can be computed as

$$\alpha^j = \frac{\mathrm{GO}^j - \sum_{s=1}^{J} X_{II}^{js}}{\sum_{b=1}^{J} \mathrm{GO}^b - \sum_{s=1}^{J} X_{II}^{bs}},$$

using for the denominator the fact that aggregate income must equal aggregate value added.

To conclude, we can now compute labor income for each commuting zone-industry pair (n, j) (as a fraction φ^j of the gross output of differentiated goods producers in this pair), as well as spending by differentiated goods producers from industry j in commuting zone n on intermediate inputs from each industry s. These numbers imply values for $X_{C,n}^j$ and $X_{II,n}^{js}$, so that we can compute the government purchase/sales share as

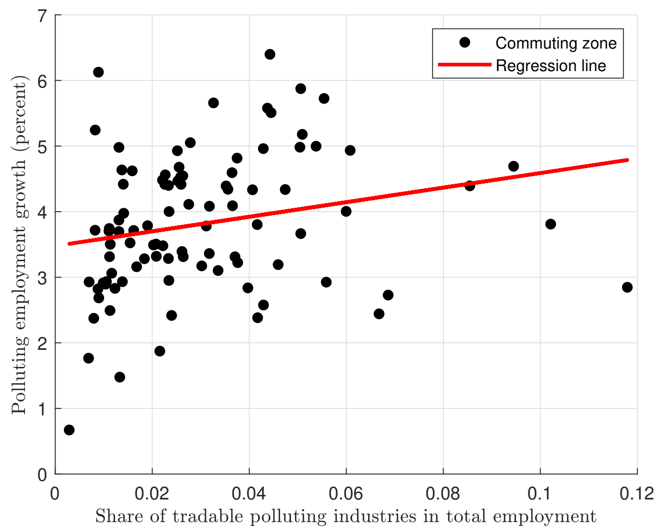
$$1-\tau_n^j = \frac{X_{C,n}^j + \sum_{s=1}^{J} X_{II,n}^{js}}{X_n^j}$$

With this, we can then finally compute, for each commuting zone-industry pair, the shares of consumption and intermediate input spending from different industries in total private spending on final goods.

D Additional model results (for online publication only)

D.1 Additional figures

Figure A.2: Specialization and polluting employment growth for attainment commuting zones



Notes: This figure plots the pre-reform employment share in tradable polluting industries for attainment commuting zones (on the x-axis) against the growth in polluting employment caused by the reform. The red line shows the fit of a simple univariate regression.

D.2 Abatement elasticities from Shapiro and Walker (2018)

In our baseline analysis, we calibrated the abatement elasticity β internally, to match our regression results for employment. As a robustness check, this section instead uses the abatement elasticity estimates from Shapiro and Walker (2018).

In their influential paper, Shapiro and Walker estimate abatement elasticities by running an instrumental variable regression of changes in emission intensity (at the county-industry level) on changes in abatement costs, instrumenting the latter with changes in county attainment status after the 1990 amendments to the Clean Air Act. This yields a unique estimate for the abatement elasticity of each pollutant in the manufacturing sector.[48] The authors then obtain industry-specific elasticities by scaling this overall value with industry-level abatement costs. We do not directly use these estimates in our baseline analysis, as they were estimated for an earlier time period (using changes in abatement between 1990

[48] Note that our abatement elasticity β corresponds to $\frac{1-\alpha}{\alpha}$ in their notation.

and 2005) and at a different level of aggregation. They also do not include the utilities industry, which is the main source of fine particle emissions.

Table A.11 explores how our results change when using the Shapiro and Walker (2018) elasticities.[49] To construct the table, we assume that utilities have the same abatement elasticity as the most polluting manufacturing industry (Primary Metals), and adjust the emission externality ψ such that we still match our regression result for overall employment growth across commuting zones. All other parameters are at their baseline values.

Table A.11: Results with abatement elasticities from Shapiro and Walker (2018)

	NA	Employment	Emp.: Polluting	Emp.: Clean	GDP/Worker
United States		-0.14%	-0.22%	-0.13%	-0.07%
Non-attainment CZs	0.76	-0.28%	-5.34%	-0.12%	-0.25%
Attainment CZs	0.00	-0.05%	2.14%	-0.14%	0.02%
Los Angeles	0.95	-0.50%	-6.38%	-0.37%	-0.33%
New York	0.99	-0.07%	-4.59%	-0.01%	-0.09%
Chicago	1.00	-0.47%	-7.36%	-0.25%	-0.38%
Newark	0.94	-0.37%	-4.73%	-0.18%	-0.36%
Boston	0.00	-0.07%	2.10%	-0.11%	0.02%
Philadelphia	0.90	-0.41%	-5.79%	-0.24%	-0.30%
Detroit	0.88	-0.06%	-6.39%	0.07%	-0.13%
San Francisco	0.00	-0.04%	2.16%	-0.09%	-0.01%
Houston	0.00	0.02%	1.32%	-0.02%	0.04%
Atlanta	0.98	-0.46%	-6.27%	-0.34%	-0.29%
Dallas	0.00	-0.05%	1.92%	-0.08%	0.00%
Minneapolis	0.00	-0.05%	1.91%	-0.09%	0.02%
Seattle	0.00	-0.08%	1.41%	-0.11%	-0.03%
Bridgeport	0.50	-0.10%	-1.78%	-0.05%	-0.10%
Phoenix	0.00	-0.05%	1.81%	-0.09%	0.01%

Notes: This table lists some key results when we use abatement elasticities from Shapiro and Walker (2018). In order to match our regression results for clean employment, we lower the value for the emission externality ψ to 0.0035. All other parameter values are the same as in our baseline calibration.

As the table shows, we find qualitatively similar results to our baseline analysis. However, the overall employment loss is now smaller, at 0.14% (against 0.25% in our baseline). This

[49] Industry-specific elasticities are listed in Table 2 of Shapiro and Walker (2018), for a generic measure of five pollutants. We scale these numbers by multiplying them with the ratio of the specific elasticity for fine particles to the generic elasticity estimated for the sample of all industries, shown in Table 1. We also convert the ISIC codes in their paper to NAICS 3-digit codes.

is due to the fact that the abatement elasticities in Shapiro and Walker (2018) are slightly larger than our estimates. However, it is worth noting that with these elasticities, we also no longer match all our regression results: our model estimate for the relative employment loss of polluting industries is now 9.3 log points, which is only half as large as the 18.59 log point reduction in our empirical estimates.

D.3 Targeting insignificant point estimates

In our empirical analysis, we found that overall employment and population growth did not significantly differ across attainment and non-attainment commuting zones after the reform. Thus, our calibration targeted a zero effect. In this section, instead, we show how our results change when we target the actual point estimates, implying a 1.6 log point decrease of employment and a 0.3 log point decrease of population in non-attainment commuting zones relative to attainment commuting zones.

Table A.12: Results with insignificant point estimates as targets

	NA	**Employment**	**Emp.: Polluting**	**Emp.: Clean**	**GDP/Worker**
United States		-0.65%	-1.02%	-0.64%	-0.34%
Non-attainment CZs	0.76	-1.81%	-11.78%	-1.49%	-1.06%
Attainment CZs	0.00	0.01%	3.96%	-0.14%	0.05%
Los Angeles	0.95	-1.85%	-14.44%	-1.57%	-1.05%
New York	0.99	-1.71%	-11.98%	-1.58%	-0.94%
Chicago	1.00	-2.01%	-15.55%	-1.60%	-1.26%
Newark	0.94	-2.45%	-11.75%	-2.06%	-1.57%
Boston	0.00	-0.02%	4.63%	-0.12%	0.06%
Philadelphia	0.90	-2.02%	-12.36%	-1.71%	-1.14%
Detroit	0.88	-1.43%	-12.84%	-1.19%	-0.85%
San Francisco	0.00	0.03%	4.47%	-0.07%	-0.02%
Houston	0.00	0.27%	3.01%	0.18%	0.14%
Atlanta	0.98	-1.87%	-14.81%	-1.59%	-0.99%
Dallas	0.00	0.04%	3.60%	-0.03%	0.02%
Minneapolis	0.00	-0.01%	3.80%	-0.10%	0.04%
Seattle	0.00	-0.08%	3.20%	-0.15%	-0.07%
Bridgeport	0.50	-1.04%	-4.79%	-0.92%	-0.62%
Phoenix	0.00	0.02%	3.40%	-0.06%	0.03%

Notes: For this table, we re-calibrate internal parameters to match the insignificant point estimates in our employment and population regressions. All other parameter values are the same as in our baseline calibration.

Table A.12 contains our results. We now find substantially larger employment losses, in line with our robustness check in Table 9 in the main text. Indeed, to match the decline in relative employment and population in non-attainment commuting zones, the calibration implies a lower emission externality, and this increases overall employment losses.

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