Regional and Aggregate Economic Consequences of the Green Transition*

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Abstract

In this paper, we evaluate the economic impact of fine particle regulations in the United States. To do so, we first provide new empirical evidence on the effects of these regulations across industries and local labour markets, and then use our regression results to calibrate a quantitative general equilibrium model. Our model implies that regulations lowered emissions by 13%, aggregate GDP per worker by 0.06% and aggregate employment by 1.55%. Aggregate employment losses are about 15% lower than the relative losses implied by our regressions. This is due to positive spillover effects from the regulations to non-regulated areas, and suggests that the employment costs of environmental regulations could be lower than previously thought.

Keywords: Pollution, Fine Particles, Clean Air Act, Employment
JEL Classification: E24, Q50, Q53

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1 Introduction

The world economy is currently in the midst of a Green Transition, with most countries making major efforts to reduce emissions of greenhouse gases and other pollutants. Nevertheless, the costs and benefits of environmental regulation remain a controversially debated topic. Our paper aims to contribute new evidence to these debates, by quantifying the economic impact of recent air pollution regulations in the United States.

In the last decades, the US Environmental Protection Agency (EPA) has repeatedly imposed strong regulations on air pollution, acting within its mandate received in the 1970 Clean Air Act. These actions have reduced emissions (Shapiro and Walker, 2018; Aldy *et al.*, 2022), but critics regularly argue that they have also destroyed jobs.[1] We re-assess these claims by studying the effects of fine particle regulations, introduced by the EPA in the early 2000s, on employment, emissions and other economic outcomes. Our approach combines microeconometric evidence with a macroeconomic model. First, we provide new regression evidence on the relative impact of the regulations across industries and local labour markets. Then, we use this evidence to calibrate a quantitative model that takes into account general equilibrium spillovers, and can therefore speak to aggregate outcomes.

To assess the relative effects of fine particle regulations, we rely on a commonly used empirical strategy, leveraging the fact that EPA regulations vary across space and time.[2] The EPA introduced fine particle regulations for the first time in 2005, by setting national air quality standards for this pollutant. Counties which were found in "non-attainment" of these standards were obliged to take steps to reduce emissions, while no actions were required in attainment counties. As the EPA standards were set at the national level, they created variation in regulation that was arguably exogenous with respect to local economic shocks. We therefore assess the relative effects of the regulatory reform by comparing outcomes between areas that became non-attainment in 2005 and areas which did not.

Given our focus on employment, we measure outcomes at the level of commuting zones, a common measure of local labour markets (see Autor *et al.*, 2013). Our main regression analysis relies on a triple difference specification. Intuitively, the direct consequences of fine particle regulations should be strongest for polluting industries (i.e., industries representing a large share of fine particle emissions) in non-attainment commuting zones. In line with this intuition, we show that after the reform, employment growth in polluting industries (relative to "clean" industries) declined more in non-attainment commuting zones than in

[1] For instance, the National Association of Manufacturers has repeatedly voiced concern (see e.g. National Association of Manufacturers, 2023).

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

attainment commuting zones. We also find some evidence for spillovers: clean industries in non-attainment commuting zones experienced lower employment growth than clean industries in attainment commuting zones, even though these effects were smaller.

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. Likewise, aggregate emissions declined more in non-attainment commuting zones. Lower emissions appeared to be due mostly to lower emission intensities (i.e., lower emissions per unit of output). This suggests that industries took abatement measures to change the way they produce, rather than just reducing the volume of production.

These empirical results are consistent with prior research, which used similar strategies to uncover negative employment effects of air pollution regulations at the plant and at the worker level (Greenstone, 2002; Walker, 2013). Our results show that the negative effects pointed out by these studies are also present for the EPA's most recent actions on fine particles, which had not been studied before. They also suggest that employment losses do not wash out at higher levels of aggregation, and might spill over to clean industries.

Our employment regression results suggest that due to the regulations, non-attainment commuting zones lost 1.6 million jobs relative to attainment commuting zones (1.83% of total employment in 1999). Importantly, however, the aggregate employment effect of the reform might not coincide with this number. Indeed, the reform might have had negative general equilibrium effects that applied equally to all commuting zones, in which case relative differences would understate its aggregate impact. Alternatively, it might also have triggered migration or a reallocation of activities 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 of emissions, employment, trade and migration across heterogeneous commuting zones. Our model extends state-of-the-art quantitative trade models (Caliendo and Parro, 2015; Caliendo *et al.*, 2019) by introducing air pollution and air pollution regulation. We assume that pollution abatement directly reduces firm-level productivity, by forcing firms to hire some workers which do not directly contribute to production. However, we assume that abatement might also create a positive externality at the commuting zone level, uniformly increasing the productivity of all firms. This externality captures the positive effects of a reduction in fine particle pollution on workers' health and therefore on their productivity.

We use our model to compare an equilibrium with low abatement costs (representing the situation before the reform) to an equilibrium with high abatement costs (representing the situation after the reform). To calibrate the model parameters, we directly use our regression results in two ways. First, we use our results on changes in emission intensity in polluting industries to infer the magnitude of the increase in abatement costs between the two equilibria.[3] Second, we calibrate two key elasticities (the strength of the emission externality and the wage elasticity of labour supply) so that our model reproduces the results of our employment regressions.

Our calibrated model indicates that regulations lowered fine particle emissions substantially, by 12.9%. This represents around one quarter of the total fall in emissions observed in the data. However, the regulations also had economic costs, lowering aggregate employment by 1.55% (or 1.36 million jobs) and GDP per worker by 0.06%. These costs are due to the negative effect of the regulations on the productivity of polluting industries, which was not compensated by a small positive externality from lower emissions.

Importantly, the change in aggregate employment is about 15% smaller than the relative employment loss suggested by our regressions. The difference between relative and aggregate numbers is explained by the fact that positive general equilibrium spillovers on attainment commuting zones (through migration and market share gains in tradable industries) outweigh negative spillovers (through higher import prices). Thus, attainment commuting zones have experienced on average a small increase in employment, compensating partly for employment losses in non-attainment commuting zones.

Related Literature A large literature has analysed the impact of the Clean Air Act (CAA) on health and economic outcomes (see Currie and Walker (2019) and Aldy *et al.* (2022) for comprehensive reviews). This literature has generally found that the CAA reduced air pollution emissions and improved health outcomes.[4]

However, researchers have also generally found a negative effect of air pollution regulation on labour 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.[5]

[3]To do so, we need to know the elasticity of emission intensity to abatement, which we take from the work of Shapiro and Walker (2018).

[4]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.

[5]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

Our empirical analysis is closely related to these studies, but considers outcomes at higher levels of aggregation, and also studies spillover effects to clean industries. Moreover, we focus on the employment effects of the EPA's regulations for fine particle emissions, which have not been studied before.[6] Our results suggest that these regulations had negative employment effects which did not wash out at the industry and local labour 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 regulation, our conclusions are strongly guided by our empirical analysis. Indeed, we calibrate several key elasticities to match our empirical 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). Most closely related to our paper are Shapiro and Walker (2018) and Hollingsworth *et al.* (2022). Shapiro and Walker (2018) structurally estimate a quantitative trade model to decompose the drivers of lower 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 Clean Air Act. Using panel regressions, they estimate the productivity losses caused by this reform in non-attainment counties, and then feed these into a quantitative trade model. They find that while the reform generated welfare gains, much higher gains could have been achieved with a first-best policy. Both papers assume full employment. Instead, our focus is on the employment impact of environmental regulations. In particular, our approach allows us to directly link microeconometric regression evidence on employment effects to a macroeconomic model, by using the identified coefficients from the former to calibrate the latter.[7]

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.

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*".

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

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

2 Institutional background and data

2.1 The Clean Air Act and regulation of fine particle emissions

The 1970 Clean Air Act (CAA) is "*arguably the most important and far-reaching environmental statute enacted in the United States*" (Aldy *et al.*, 2022).[8] Among many other provisions, it empowered the EPA to set National Ambient Air Quality Standards (NAAQS) for several air pollutants, including sulfur dioxide (SO_2), nitrogen oxides (NO_x), carbon monoxide (CO) or particulate matter (including fine particles, $PM_{2.5}$).

The EPA defines a threshold value for the atmospheric concentration of each regulated pollutant, based on public health considerations. Using data from monitoring stations, it then determines once a year whether counties are in attainment or non-attainment of these thresholds. State governments must 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 set industry-specific regulations for non-attainment counties, e.g. by requiring plants to adopt technologies with the "lowest achievable emissions rate".

Crucially, both the thresholds and the type of pollutants included in the NAAQS change over time. Our paper focuses on fine particles, as this pollutant has seen the most regulatory changes in the last three decades. Prompted by increasing evidence for the negative health consequences of exposure to fine particles (which can cause or amplify a variety of heart and lung conditions),[9] the EPA introduced the first NAAQS thresholds for this pollutant in 1997.[10] However, implementation was delayed to January 2005, when the EPA started classifying counties as in attainment or non-attainment of the new thresholds. Thresholds were tightened further in 2006 (implemented in 2009) and 2012 (implemented in 2015).[11]

Our empirical analysis compares outcomes between non-attainment and attainment areas. Given our focus on local labour markets, we conduct our analysis at the commuting zone level. We obtain data for the attainment status of counties from the EPA's Green Book, and map counties to commuting zones using the correspondence table created by

[8] Currie and Walker (2019) and Aldy *et al.* (2022) provide a more detailed description. The CAA is also the legal basis of fuel standards for cars and cap-and-trade programs for certain pollutants.

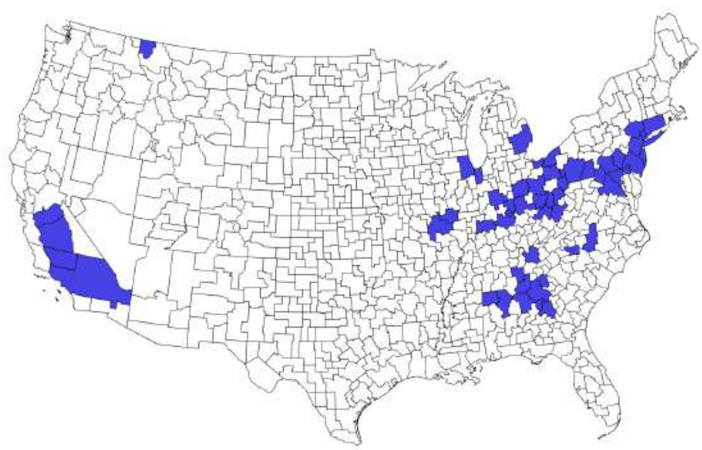
[9] The Global Burden of Disease project has estimated that fine particles caused 47'800 deaths in the United States in 2019 (see `https://www.healthdata.org/research-analysis/gbd`).

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

[11] A timeline of the NAAQS for fine particles is available at `https://www.epa.gov/pm-pollution/timeline-particulate-matter-pm-national-ambient-air-quality-standards-naaqs`.

Autor and Dorn (2013). For our baseline analysis, we consider a commuting zone to be non-attainment if at least one third of its population resides in a non-attainment county, as in Vona *et al.* (2019). In turn, non-attainment counties are all counties classified as fully or partially non-attainment by the EPA. Our results are robust to alternative definitions.

Throughout, we focus on changes in attainment status when fine particle regulation was first introduced, and refer to this event as "the reform". At that moment, 54 of the 741 commuting zones in the United States (shown as shaded areas in Figure 1) were classified as non-attainment. The tighter standards of 2009 and 2015 affected much fewer commuting zones, and there were no changes in attainment status in all other years.[12] Moreover, we follow Bishop *et al.* (2022), who study the effect of fine particle exposure on dementia, and consider 2004 as the effective starting date of the regulations. Indeed, 2005 attainment status was based on atmospheric concentrations measured between 2001 and 2003, and by early 2004, state governments knew the future attainment status of each county.



Notes: This map shows all commuting zones in the United States, with the exception of those located in Alaska or Hawai'i. Shaded commuting zones were classified as non-attainment for fine particles in 2005.

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

Clearly, non-attainment status was not randomly assigned: affected commuting zones tended to be larger and more urban. Nevertheless, there still is substantial variation across urban commuting zones (for instance, Los Angeles, Philadelphia and Detroit were classified as non-attainment, while San Francisco, Boston and Houston were not). Moreover, note

[12] 14 commuting zones became non-attainment in 2009, and 3 in 2015. In our analysis, we omit these commuting zones, in order to avoid the issues caused by staggered treatment (see Borusyak *et al.*, 2021).

that non-attainment status appears to depend on persistent commuting zone characteristics: no commuting zone ever switches into non-attainment in a year without NAAQS changes. In our regressions, we control for time-invariant commuting zone-industry characteristics (as well as for industry and commuting zone time trends).

2.2 Air pollution emissions

To measure air pollution emissions, we rely on the EPA's National Emissions Inventory (NEI), which records emissions of several pollutants at the plant level. We aggregate its data for primary fine particle emissions to the commuting zone-industry level.[13] Our industry classification follows the BEA's national industry accounts and has 60 industries, corresponding roughly to three-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). Aggregate fine particle emissions have declined by 72% over the period, while the aggregate emission intensity (i.e., the ratio of emissions to aggregate real value added) has declined by about 80%.

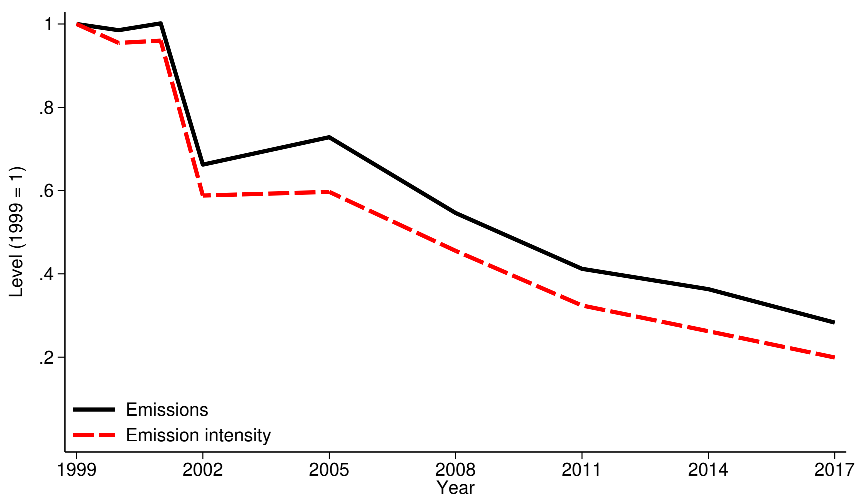


Figure 2: Trends in fine particle emissions

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

[13] 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.

Fine particles are mainly created through the combustion of gasoline, oil, diesel fuel or wood. Thus, emissions are concentrated in a relatively small number of industries. For our baseline analysis, we will consider as "polluting" the industries which represent more than 5% of national fine particle emissions in 1999, the first year of our analysis. There are four such industries: Utilities (NAICS Code 221), Primary metals (331), Paper products (322) and Non-metallic mineral products (327). Together, these industries account for 72% of fine particle emissions in 1999. Thus, one would imagine that they are most directly affected by the EPA regulations. In contrast, industries that hardly emit any fine particles (such as most services) can only be indirectly affected.

2.3 Employment and other economic outcomes

We obtain annual data for employment at the county-industry level between 1999 and 2019 from the US Census Bureau's County Business Patterns (CBP). Again, we aggregate county data to commuting zones using the correspondence table of Autor and Dorn (2013).

As we do not directly observe value added at the commuting zone level, we obtain industry-level data for real value added from the BEA and use this to construct a proxy for value added at the commuting zone-industry level, splitting up the national data using employment weights from our CBP data. Finally, we obtain data on commuting zone population from the Bureau of Labor Statistics (BLS). Further details on all data sources can be found in Appendix A.

3 Empirical analysis

3.1 Employment at the commuting zone-industry level

We start by analysing the effects of fine particle regulations on employment, our main outcome of interest.

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 commuting zones relative to attainment commuting zones (second difference), and for polluting relative to clean industries (third difference). Accordingly, we estimate

$$\ln L_{n,t}^{j} = \sum_{y=1999}^{2019} \gamma_y \cdot \left(\mathbb{1}_n^{\mathrm{NA}} \cdot \mathrm{Emit}_{1999}^{j} \cdot \mathbb{1}_{y,t} \right) + \alpha_n^j + \alpha_t^j + \alpha_{n,t} + \epsilon_{n,t}^{j}. \tag{1}$$

In this specification, $L_{n,t}^{j}$ stands for employment in commuting zone n and industry j in year t. $\mathbb{1}_n$ is a dummy equal to 1 if commuting zone n was classified as non-attainment for fine particles in 2005. Emit_{1999}^{j} is a dummy equal to 1 if industry j represents more than 5% of national emissions of fine particles in 1999. Finally, $\mathbb{1}_{y,t}$ is a year dummy for year y. The coefficients of interest are the (year-specific) coefficients for the interaction between commuting zone non-attainment status and the industry emitter status, 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 have lower employment growth than clean ones. The specification controls for commuting zone-industry, industry-year and commuting zone-year fixed effects.[14] We weight observations by commuting zone-industry employment in 1999, and cluster standard errors by commuting zone.

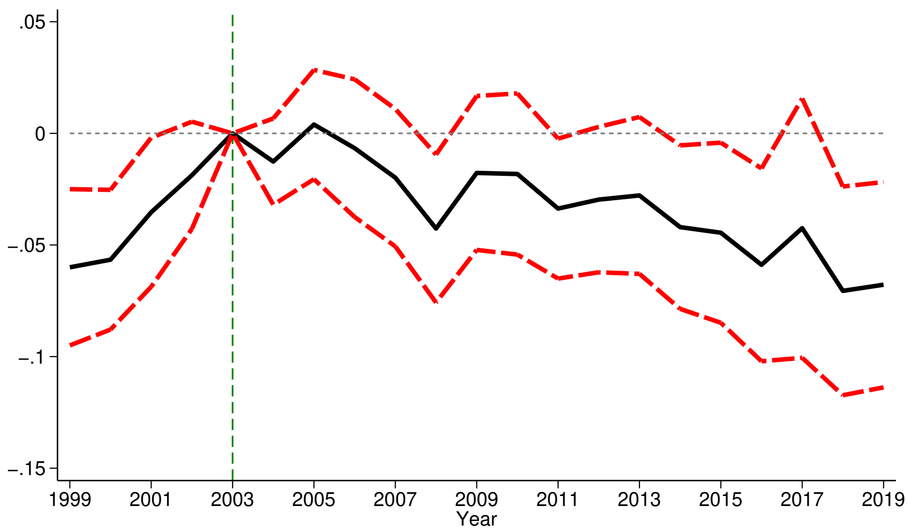


Figure 3: The effect of fine particle regulations on employment in polluting industries

Notes: The solid black line plots the coefficients γ_y from an estimation of the model specified in equation (1). Red dashed lines indicate 90% confidence intervals. Observations are weighted by commuting zone-industry employment in 1999, and standard errors are clustered by commuting zone.

Figure 3 illustrates the results of these regressions. 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

[14]The fixed effects absorb all two-way interactions. In robustness checks, we will drop some fixed effects, allowing us to reintroduce some two-way interactions.

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 (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 0.06 log points by 2019.

To analyse the change in trend more formally, we consider a triple difference model in growth rates. Precisely, we estimate

$$\ln L_{n,t}^{j} - \ln L_{n,t-1}^{j} = \gamma \cdot \left(\mathbb{1}_{n}^{\text{NA}} \cdot \text{Emit}_{1999}^{j} \cdot \mathbb{1}_{t}^{\text{Post}} \right) + \alpha_{n}^{j} + \alpha_{t}^{j} + \alpha_{n,t} + \epsilon_{n,t}^{j}, \tag{2}$$

where $\mathbb{1}_{t}^{\text{Post}}$ is an indicator variable equal to 1 if year t is a post-reform year (i.e., 2004 or later). Table 1 shows the results for this regression.

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

	(1)	(2)	(3)	(4)	(5)
NA x Emitter x Post	-0.016***	-0.014***	-0.011**	-0.010**	-0.071***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.017)
NA x Post		-0.003***		-0.000	
		(0.001)		(0.001)	
Industry-year FE	Yes	Yes	Yes	Yes	Yes
CZ-industry FE	Yes	Yes	Yes	Yes	Yes
CZ-year FE	Yes	No	Yes	No	Yes
N	473572	473627	473572	473627	473572
R^2	0.283	0.236	0.283	0.236	0.283

Notes: Column (1) shows our estimates for the specification in equation (2). Columns (2) and (4) drop commuting zone-year fixed effects and introduce the interaction between the non-attainment dummy and the post-reform dummy as an explanatory variable. Columns (3) and (4) use a different definition of attainment (explained in the main text), and column (5) uses a continuous measure for polluting industries. The dependent variable is winsorized to be between -1 and 1 log points. Observations are weighted by commuting zone-industry employment in 1999. Standard errors clustered by commuting zone in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The first column shows the results for the specification in equation (2). After the reform, the relative employment growth rate in polluting industries (with respect to clean industries) is about 1.6 percentage points lower in non-attainment commuting zones. This is a substantial effect, in line with the empirical evidence on earlier air pollution regulations.[15]

Columns (2) to (5) of Table 1 illustrate alternative specifications. In column (2), we drop commuting zone-year fixed effects, so that we can introduce the interaction between non-attainment status and the post-reform dummy, and thereby estimate the effect of the reform on relative employment in clean industries. We find a mild negative effect for these: after the reform, employment growth in clean industries drops by 0.3 percentage points in non-attainment commuting zones relative to attainment commuting zones. In turn, in this specification, relative employment growth in polluting industries drops by 1.7 percentage points $(1.4 + 0.3)$ in non-attainment commuting zones. We consider results from this specification as our baseline results, and will rely on them to calibrate our model.

In columns (3) and (4), we reproduce the results from the first two columns using an alternative attainment definition: now, we consider a commuting zone as non-attainment if at least one third of its population lives in fully non-attainment counties (while our baseline considered either fully or partially non-attainment counties). Results for polluting industries are similar to the baseline, although the coefficients are somewhat lower. However, the spillover effect on clean industries is now no longer economically or statistically significant. Finally, in column (5), we replace the polluting industry dummy with a continuous variable, equal to the share of industry j in 1999 emissions. Again, we find that more polluting industries have lower post-reform employment growth.

Using these results, we can compute an estimate for the relative employment losses caused by the reform (in line with Greenstone, 2002). To do so, we consider a 14-year horizon after the reform, and the coefficients from our baseline results in column (2) of Table 1. Multiplying these estimates with the aggregate employment of polluting and clean industries in non-attainment commuting zones, we obtain that non-attainment commuting zones lost 1.6 million jobs relative to attainment commuting zones. This corresponds to 1.83% of aggregate employment in 1999. If employment in attainment commuting zones was not affected by the reform, this would also be the aggregate employment loss. However, in the presence of general equilibrium spillovers, the aggregate loss could be larger or smaller. We will explore this question in our quantitative analysis.

3.2 Fine particle emissions in polluting industries

Next, we analyze the effect of the EPA regulations on fine particle emissions. This is interesting in its own right, and will also be useful for estimating the magnitude of the

[15] 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.

abatement shocks that we will feed into our quantitative model.

To study emissions, we concentrate on polluting industries, and use a difference in difference analysis. Intuitively, we would expect that after the reform, emissions of polluting industries fall more strongly in non-attainment commuting zones.[16] To test this hypothesis, we estimate

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

where $E^{j}_{n,t}$ stands for the fine particle emissions of industry j in commuting zone n in year t. All other variables are defined as before.[17] We estimate this equation using only data from polluting industries (defined as in our employment analysis), and weight observations by emissions in 1999, the initial year of our analysis. As emissions are only observed in 3-year intervals after 2002, we consider three-year growth rates.

Table 2 shows the results from this regression. Column (1), containing the baseline specification, shows a large and statistically significant drop in the emissions of polluting industries in non-attainment commuting zones after the reform.

Table 2: The effect of fine particle regulations on emissions

	(1)	(2)	(3)	(4)
NA x Post	-0.416**	-0.466***	-0.594***	-0.412**
	(0.171)	(0.167)	(0.168)	(0.174)
Industry-year FE	Yes	Yes	Yes	Yes
CZ-industry FE	Yes	Yes	Yes	Yes
N	6736	5061	2638	6736
R^2	0.200	0.196	0.153	0.200

Notes: This table shows estimates for the specification in equation (3). The dependent variable is winsorized between -3 and 3 log points (i.e., an annual growth rate between -1 and 1 log points). Observations are weighted by commuting zone-industry emissions in 1999. Standard errors clustered by commuting zone in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Column (2) considers only the three most polluting industries, and column (3) only the most polluting industry (utilities). Estimates are even larger, indicating that the most polluting industries experienced the greatest reductions in emissions. Finally, in column (4), we use our alternative definition of non-attainment introduced in Section 3.1, considering only fully non-attainment counties. Results are virtually identical to the baseline.

[16] For emission outcomes, a triple difference analysis as for employment does not seem appropriate: as clean industries emit no or little fine particles, they are not a meaningful comparison group.

[17] Accordingly, we consider emissions growth between 2002 and 2005 as being post-reform.

Reductions in emissions can be achieved either through a reduction in production, or a reduction in the emission intensity of production. The difference in magnitude between our results for employment and emissions suggests that the largest part of the emission reductions must have come through lower emission intensity. To test this formally, Table 3 shows estimation results when replacing the dependent variable in equation (3) by emission intensity, i.e., the ratio of emissions to real value added.

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

	(1)	(2)	(3)	(4)
NA x Post	-0.335*	-0.385**	-0.467**	-0.310
	(0.199)	(0.191)	(0.217)	(0.207)
Industry-year FE	Yes	Yes	Yes	Yes
CZ-industry FE	Yes	Yes	Yes	Yes
N	4851	3444	2071	4851
R^2	0.209	0.203	0.165	0.209

Notes: This table shows estimates for the specification in equation (3), using emission intensity as the dependent variable. The dependent variable is winsorized between -3 and 3 log points (i.e., an annual growth rate between -1 and 1 log points). Observations are weighted by commuting zone-industry emissions in 1999. Standard errors clustered by commuting zone in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Results in Table 3 are similar to those in Table 2, just somewhat smaller in magnitude. They indicate that for polluting industries in non-attainment commuting zones, emission intensity fell after the introduction of the EPA regulation, presumably because of abatement measures imposed by the regulators.

3.3 Commuting-zone level results

Finally, we can analyse aggregate changes at the commuting zone level. This has the advantage of taking into account within-commuting zone general equilibrium effects, but our regressions will also contain less controls, and thus be more vulnerable to biases.

For commuting zone outcomes, we use a simple difference in difference analogue to our triple difference model for employment, estimating

$$\ln O_{n,t} = \sum_{y=1999}^{2019} \gamma_y \cdot \left(\mathbb{1}_n^{\text{NA}} \cdot \mathbb{1}_{y,t} \right) + \alpha_n + \alpha_t + \epsilon_{n,t}. \tag{4}$$

where $O_{n,t}$ is an outcome (such as emissions or employment) in commuting zone n at time t. Figure 4 shows illustrates our results for fine particle emissions (as emissions data is available every three years, we cannot treat the interaction for the year 2003 as the omitted category, and instead choose the year 2002). The figure shows that before the reform, emissions were growing faster in non-attainment commuting zones (although non statistically significantly so). After the reform, this trend reversed, and there was a large and statistically significant decline in the relative emissions of non-attainment commuting zones, adding up to 0.6 log points by 2017.

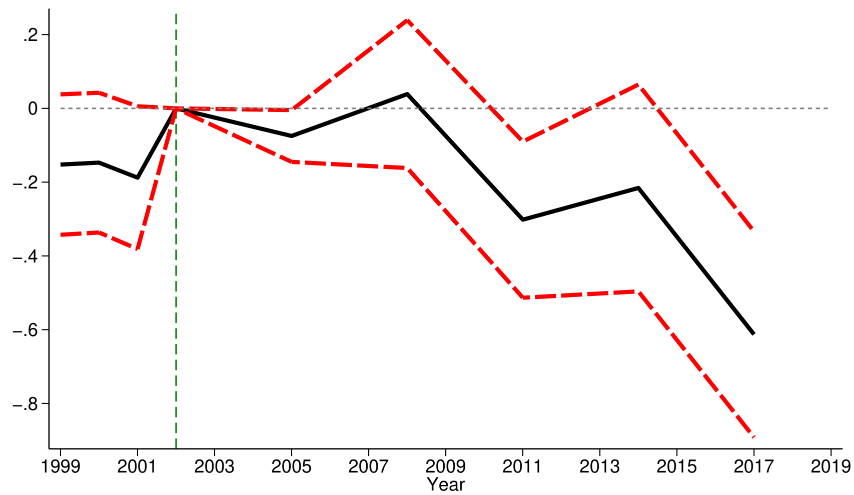


Figure 4: Commuting zone emissions over time

Notes: The solid black line plots the estimated coefficients γ_y from equation (4), with fine particle emissions as the dependent variable. Red dashed lines indicate 90% confidence intervals. Observations are weighted by commuting zone emissions in 1999, and standard errors are clustered by commuting zone.

Figure 5, in turn, considers employment as a dependent variable. The figure indicates that after the reform, the relative employment of non-attainment commuting zones fell, but also that this appears to have been the continuation of an earlier trend. Estimating a difference in difference model for growth rates along the lines of equation (3) shows no statistically significant difference between employment growth before and after the reform. However, the higher level of aggregation also does not allow us to control for as many confounding factors as in our commuting zone-industry level regressions, so that these results should be taken with a grain of salt.

Summing up, our empirical analysis suggests that the EPA's fine particle regulations have had a negative effect on the relative emissions and employment of polluting industries. There is also some evidence for a small negative spillover on employment in clean industries. 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, the next section

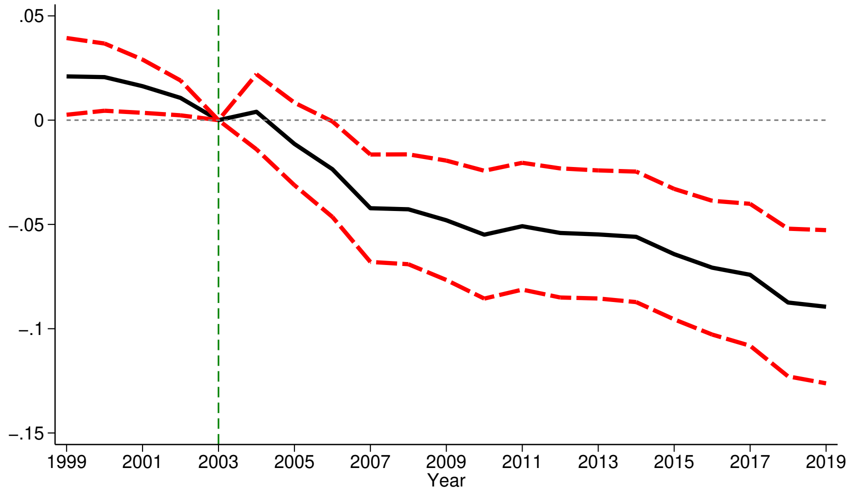


Figure 5: Commuting zone employment over time

Notes: The solid black line plots the estimated coefficients γ_y from the model specified in equation (4), with employment as the dependent variable. Red dashed lines indicate 90% confidence intervals. Observations are weighted by employment in 1999, and standard errors are clustered by commuting zone.

introduces a model that takes into account general equilibrium forces.

4 Model

4.1 Assumptions

Our model builds on the recent literature on quantitative trade models with labour mobility (see e.g. Caliendo *et al.*, 2019). However, we add several new elements to this setup, such as endogenous labour supply, air pollution emissions, and pollution abatement.

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

Each worker 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 labour to supply in this commuting zone and industry. Her utility is given by

$$u_h = \max_{n,j} \left[\iota_n^j + \eta_{n,h}^j + \max_{\ell_{n,h}^j} \left[\ln \left(c_{n,h}^j - \frac{1}{1+\zeta} \left(\ell_{n,h}^j \right)^{1+\zeta} \right) \right] \right], \qquad (5)$$
$$\text{such that } \; P_n c_{n,h}^j = w_n^j \ell_{n,h}^j.$$

In this expression, $c_{n,h}^{j}$ stands for the consumption of the household, expressed in units of the unique final good of the commuting zone she lives in, and $\ell_{n,h}^{j}$ stands for her labour supply. Labour supply depends on the prevailing wage in the commuting zone-industry pair, w_n^j, the price of the final good in the commuting zone, P_n, and the positive parameter ζ, capturing the inverse elasticity of labour supply. 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, $\eta_{n,h}^{j}$. Following Rodríguez-Clare *et al.* (2020), we assume that each household draws a vector of idiosyncratic preferences $\boldsymbol{\eta} = \left[\eta_1^1, ..., \eta_N^J\right]$ from a nested Gumbel distribution with a joint cumulative distribution function

$$G\left(x_1^1, ..., x_N^J\right) = \exp\left(-\sum_{n=1}^{N}\left(\sum_{j=1}^{J}\exp\left(-\frac{x_n^j}{\nu}\right)\right)^{\frac{\nu}{\kappa}}\right). \tag{6}$$

Preference draws are i.i.d. across households. As we will see later, the positive parameter κ governs how easily workers move between commuting zones, while the positive parameter ν governs how easily they move between industries within a commuting zone.

Production In each commuting zone n, the non-tradable final consumption good is assembled as a Cobb-Douglas aggregate of the final output of the J different industries:

$$Y_n = \prod_{j=1}^{J}\left(Y_n^j\right)^{\alpha^j}, \tag{7}$$

where Y_n stands for the output of the final consumption good in commuting zone n, Y_n^j stands for the final output of industry j in commuting zone n, and α^j stands for the spending share of industry j. Spending shares are positive and hold $\sum_j \alpha^j = 1$.

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

$$Y_n^j = \left(\int_0^1 \left(r_n^j(\omega)\right)^{\frac{\varepsilon-1}{\varepsilon}} d\omega\right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{8}$$

where $r_n^j(\omega)$ stands for the use of good ω of industry j in commuting zone n, and ε is the elasticity of substitution between goods.

Good ω of industry j can be produced in any commuting zone n, with a production technology using only labour. The production function is given by

$$y_n^j(\omega) = \tilde{z}_n^j(\omega) \cdot \ell_n^j(\omega), \text{ where } \tilde{z}_n^j(\omega) \equiv E_n^{-\psi} \cdot \lambda_n^j \cdot z_n^j(\omega). \tag{9}$$

In this expression, $\ell_n^j(\omega)$ stands for the number of workers hired by firms producing good ω. The productivity of these workers, $\tilde{z}_n^j(\omega)$, depends on three components:

1. **An emission externality $E_n^{-\psi}$.** This externality is common across all firms in a commuting zone, and depends on total commuting zone emissions E_n. We assume that $\psi \geq 0$, so that emissions have a negative effect on productivity.[18] As each firm is atomistic, it takes E_n as given.

2. **An emission abatement $1 - \lambda_n^j$.** Firms might be required to abate emissions. We assume that each worker needs to devote a fraction $1 - \lambda_n^j$ of her time to abatement, so that only the remaining fraction λ_n^j of her time is available for production.

3. **An idiosyncratic productivity $z_n^j(\omega)$.** Idiosyncratic productivities in industry j of commuting zone n 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 productivity dispersion.

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 good of industry j from commuting zone i to commuting zone n, firms need to ship d_{ni}^j units of the good. Firms hire workers on a competitive labour market that is commuting zone-industry specific, and sell their goods under perfect competition.

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

$$\frac{e_n^j(\omega)}{y_n^j(\omega)} = \sigma_n^j \cdot \left(\lambda_n^j\right)^{\beta^j}, \tag{10}$$

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

[18] Empirical studies have shown that air pollution increases sick leave and decreases cognitive ability (Dechezleprêtre *et al.*, 2019). Air pollution can also have a negative impact on children's health, with long-lasting negative effects (Klauber *et al.*, 2023). Note that our assumption of a commuting zone-level externality is appropriate for the pollutants we consider here, as their effect is indeed local. This assumption would be less appropriate for modeling emissions of greenhouse gases such as CO_2 or methane.

positive parameter σ_n^j, capturing technology, is the emission intensity that would prevail without any abatement. More abatement (i.e., a reduction in workers' fraction of time spent in production λ_n^j) lowers the emission intensity, with the industry-specific elasticity parameter β^j governing the strength of this effect.

We assume throughout that the abatement parameters λ_n^j are exogenously set by policy makers. As equation (10) shows, this is isomorphic to policy makers mandating an emission intensity for each commuting zone-industry.[19]

Trade deficits In the model laid out so far, commuting zone spending would be equal to income. However, in real-world data, spending and income are different, as commuting zones have trade surpluses or deficits. To accommodate these, we assume that besides workers, each commuting zone is also populated by a mass 1 of retirees. Retirees cannot move between commuting zones. They receive a fixed pension equal to T units of the consumption good, financed by a lump-sum tax that falls equally on all worker households. Retirees make transfers to retirees in other commuting zones. The net transfer received by commuting zone n, denoted by D_n, is specified as a fixed fraction of the total income in commuting zone n,

$$D_n = \chi_n w_n L_n, \tag{11}$$

where $w_n L_n \equiv \sum_{j=1}^{J} w_n^j L_n^j$ is the total income of commuting zone n and $\sum_{n=1}^{N} D_n = 0$.

4.2 Equilibrium conditions in relative changes

We aim to use our model to study the effect of the introduction of fine particle regulations. To do so, we compare the pre-reform equilibrium of our model to its 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 all derivations in Appendix B.

Households We denote by M_n^j the mass of workers in commuting zone n and industry j, and by M_n the total mass of workers in commuting zone n (i.e., the total labour force of the commuting zone, holding $M_n \equiv \sum_{j=1}^{J} M_n^j$). Changes in the within-commuting zone

[19] To be precise, this statement is true as long as policy makers do not want to achieve an emission intensity higher than the fundamental value σ_n^j. However, this case is irrelevant in practice.

distribution of workers across industries hold

$$\frac{\widehat{M}_n^j}{\widehat{M}_n} = \frac{\left(\widehat{w}_n^j\right)^{\frac{1+\zeta}{\nu\zeta}}}{\sum_{s=1}^{J} \frac{M_n^s}{M_n} \left(\widehat{w}_n^s\right)^{\frac{1+\zeta}{\nu\zeta}}}. \tag{12}$$

Changes in the allocation of workers across industries are due to changes in nominal wages: industries in which the nominal wage increases with respect to the commuting zone average attract relatively more workers. The parameter $1/\nu$ captures the elasticity of industry switches with respect to changes in relative wages. When this elasticity is low, the labour force allocation does not react much to a change in wages. Likewise, a low labour supply elasticity $1/\zeta$ also dampens the effect of wages on the labour force allocation.

Changes in the total labour force in a commuting zone hold

$$\widehat{M}_n = \frac{\left(\sum_{j=1}^{J} \frac{M_n^j}{M_n} \left(\frac{\widehat{w}_n^j}{\widehat{P}_n}\right)^{\frac{1+\zeta}{\nu\zeta}}\right)^{\frac{\nu}{\kappa}}}{\sum_{i=1}^{N} M_i \left(\sum_{j=1}^{J} \frac{M_i^j}{M_i} \left(\frac{\widehat{w}_i^j}{\widehat{P}_i}\right)^{\frac{1+\zeta}{\nu\zeta}}\right)^{\frac{\nu}{\kappa}}}. \tag{13}$$

These changes are triggered by changes in relative real wages: commuting zones in which real wages rise with respect to the average see their labour force increase. The size of these changes depends on the switching elasticity $1/\kappa$: with a low switching elasticity, changes in real wages only have a small impact on the distribution of the labour force across commuting zones. In contrast, when the switching elasticity is high, even a small change in real wages can trigger a large reallocation.

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

$$\widehat{L}_n^j = \widehat{M}_n^j \left(\frac{\widehat{w}_n^j}{\widehat{P}_n}\right)^{\frac{1}{\zeta}}. \tag{14}$$

Our analysis considers labour supply as the model equivalent to employment in the data.[20] Equation (14) shows that changes in labour supply are driven both by an extensive

[20] Caliendo *et al.* (2019) assume that households supply labour inelastically, but can choose to locate in a home production industry. In contrast, our approach 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.

margin (a change in the number of worker households in the commuting zone-industry) and an intensive margin (a change in the labour supplied by each worker, in response to the change in the real wage).

Production Our assumptions on production, summarized in equation (9), imply that both the emissions externality and abatement affect all firms of a commuting zone-industry in the same way. Thus, firm productivity $\widetilde{z}_n^j$ follows a Fréchet distribution, with parameters (T_n^j, θ^j).[21] Changes in abatement do not affect the dispersion of the distribution, but they do affect the level parameter, which holds

$$\widehat{T}_n^j = \left(\widehat{E}_n\right)^{-\psi\theta^j} \left(\widehat{\lambda}_n^j\right)^{\theta^j}. \tag{15}$$

Thus, average productivity in a commuting zone-industry decreases with abatement (which implies that workers spend less time on production) 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 commuting zone n in industry j that is spent on goods of commuting zone i, we have

$$\widehat{\pi}_{ni}^j = \frac{\widehat{T}_i^j \left(\widehat{w}_i^j\right)^{-\theta^j}}{\sum_{k=1}^{N} \pi_{nk}^j \widehat{T}_k^j \left(\widehat{w}_k^j\right)^{-\theta^j}}. \tag{16}$$

That is, in any industry j, commuting zone n spends more on goods from commuting zone i if there is an decrease in the relative costs of that commuting zone with respect to all others. Costs depend negatively on productivity T_i^j and positively on wages w_i^j.

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

$$\widehat{P}_n^j = \left(\sum_{i=1}^{N} \pi_{ni}^j \widehat{T}_i^j \left(\widehat{w}_i^j\right)^{-\theta^j}\right)^{-\frac{1}{\theta^j}}. \tag{17}$$

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

$$\widehat{P}_n = \prod_{j=1}^{J} \left(\widehat{P}_n^j\right)^{\alpha^j}. \tag{18}$$

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

Finally, nominal income in each commuting zone-industry pair holds

$$\widehat{w}_n^j \widehat{L}_n^j = \sum_{i=1}^{N} s_{ni}^j \widehat{\pi}_{in}^j \widehat{w_i L_i}, \tag{19}$$

where

$$\widehat{w_i L_i} = \sum_{s=1}^{J} \frac{w_i^s L_i^s}{w_i L_i} \widehat{w}_i^s \widehat{L}_i^s \quad , \quad s_{ni}^j \equiv \frac{\pi_{in}^j (1+\chi_i) w_i L_i}{\sum_{k=1}^{N} \pi_{kn}^j (1+\chi_k) w_k L_k}. \tag{20}$$

Nominal income is the product of the nominal wage and employment. Changes in the nominal income of each commuting zone-industry pair - the left-hand side of equation (19) - must be equal to changes in the spending on goods from this commuting zone-industry pair - the right-hand side of equation (19). Changes in spending are a weighted average of changes in spending shares and changes in the overall income of destination commuting zones, where the weights are given by initial sales shares.[22]

Emissions Finally, for every commuting zone n, the change in emissions is given by

$$\widehat{E}_n = \sum_{j=1}^{J} \frac{E_n^j}{E_n} \left(\widehat{\lambda}_n^j\right)^{\beta^j} \sum_{i=1}^{N} \widetilde{s}_{ni}^j \widehat{\pi}_{in}^j \frac{\widehat{w_i L_i}}{\widehat{P}_i^j}, \ \text{ with } \ \widetilde{s}_{ni}^j = \frac{d_{in}^j \pi_{in}^j (1+\chi_i) w_i L_i / P_i^j}{\sum_{k=1}^{N} d_{kn}^j \pi_{kn}^j (1+\chi_k) w_k L_k / P_k^j}. \tag{21}$$

The change in emissions is a weighted average of changes in industry-level emissions. Industry-level emissions change because of changes in abatement (which changes emission intensities) and changes in scale. These changes in scale are computed analogously to changes in spending, but they refer to changes in physical rather than nominal output (as emissions only depend on physical quantities).[23]

Solving the model The model solution algorithm is described in Appendix B. Intuitively, given changes in abatement $\widehat{\lambda}_n^j$ and changes in commuting-zone level emissions $\widehat{E}_n$, we know productivity changes for each commuting zone-industry pair. Then, knowing initial labour force shares M_n^j, spending shares π_{in}^j, sales shares s_{ni}^j and commuting zone incomes $w_n L_n$, equation (19) defines a system of $NJ-1$ equations in $NJ-1$ unknowns (normalizing the change in nominal wages in one commuting zone-industry pair to 1). This system can be

[22]Precisely, s_{ni}^j is the share of total sales of commuting zone n in industry j that go to commuting zone i.

[23]Accordingly, $\widetilde{s}_{ni}^j$ is the analogue of s_{ni}^j: the share of output produced in commuting zone n and industry j that is shipped to commuting zone i. Note that these shares include the iceberg trade costs.

solved numerically, yielding changes in nominal wages for each commuting zone-industry. These changes in nominal wages then pin down changes in prices, real wages, employment and labour force shares.

However, as we do not know emission changes a priori, we need to use an iterative algorithm. First, we guess a value for emission changes in every commuting zone. Then, we compute the corresponding changes in productivity and solve for the equilibrium. Using this solution, we compute the implied change in emissions using equation (21). If these implied changes correspond to our initial guess, we have found the equilibrium, if not, we update our guess for the change in emissions and reiterate.

5 Calibration

In the remainder of this paper, we use our model to estimate the aggregate effects of the EPA's fine particle regulations. The discussion in the previous section shows that in order to calibrate the model and solve for its predictions, we need (a) an estimate of the change in abatement costs induced by the regulations, (b) some key characteristics of the pre-reform equilibrium (e.g. the initial distribution of the labour force and trade flows), and (c) values for the model elasticities. We now explain how we obtain these numbers.

5.1 Changes in abatement costs

Throughout, we consider the year 1999 as corresponding to the model's pre-reform equilibrium, and the year 2017 as corresponding to the model's post-reform equilibrium. Through the lens of the model, the reform corresponds to a change in abatement costs for every commuting zone-industry pair, $\widehat{\lambda}_n^j$. Thus, first of all, we need to identify these changes in abatement costs.

To do so, we rely on the structure imposed by our model. Within each commuting zone-industry pair, all firms have the same emission intensity. Therefore, the industry-level emission intensity holds

$$\frac{E_n^j}{\widetilde{Y}_n^j} = \sigma_n^j \cdot \left(\lambda_n^j\right)^{\beta^j}, \tag{22}$$

where $\widetilde{Y}_n^j$ stands for the total physical output of the industry. Thus, changes in industry-level emission intensity are directly related to changes in abatement:

$$\ln \widehat{\left(\frac{E_n^j}{\widetilde{Y}_n^j}\right)} = \beta^j \ln\left(\widehat{\lambda}_n^j\right). \tag{23}$$

Building on this relationship, we impose two further assumptions, in line with the institutional setup and our empirical analysis in Section 3. First, we assume that the EPA's actions only triggered changes in abatement for polluting industries in non-attainment commuting zones. Second, we assume that in imposing this abatement, policy makers aimed for a uniform reduction in emission intensity across all commuting zones and polluting industries. Then, for every polluting industry j, we can write the change in emission intensity caused by the EPA's actions as

$$\ln \widehat{\left(\frac{E_n^j}{\widetilde{Y}_n^j}\right)} = \ln \left(\frac{E_n^{j\prime}}{\widetilde{Y}_n^{j\prime}}\right) - \ln \left(\frac{E_n^j}{\widetilde{Y}_n^j}\right) = \gamma^{\text{NA}} \cdot \mathbb{1}_n^{\text{NA}}, \tag{24}$$

where $\mathbb{1}_n^{\text{NA}}$ is a dummy equal to 1 if commuting zone n is non-attainment, and γ^{NA} is a parameter.

Equation (24) is the exact equivalent, for a single time period, of our empirical difference in difference estimation for emission intensity, specified in equation (3). We found (in column (1) of Table 3) that after the reform, the 3-year growth rate of emission intensity for polluting industries in non-attainment commuting zones was 0.335 log points lower than the one for polluting industries in attainment commuting zones. Scaling this estimate up to a 14-year period (the number of years between the introduction of the reform in 2004 and our post-reform year 2017) gives $\gamma^{\text{NA}} = {}^{14}/_{3} \cdot 0.335 = 1.563$. In words, our empirical estimates imply that over a 14-year period, polluting industries in non-attainment commuting zones reduced their emission intensity by 1.563 log points.[24]

Using this estimate, equation (24) shows that we can deduce our object of interest, the abatement cost shocks $\widehat{\lambda}_n^j$, if we know the parameters β_j, i.e., the industry-specific elasticities of emission intensity with respect to abatement. We take these elasticities from Shapiro and Walker (2018), who estimated them using data on abatement costs.[25]

Table 4 summarizes our estimated abatement shocks (which, by definition, only apply to polluting industries, and are common across non-attainment commuting zones). Recall

[24]The relative change in emission intensity is equal to the absolute one, as we assume that polluting industries in attainment commuting zones are unaffected by the reform. This is consistent with our model, where there are indeed no general equilibrium spillovers for emission intensity (although there are of course such spillovers for the level of emissions or employment).

[25]Note that our parameter β_j corresponds to ${}^{1-\alpha_s}/_{\alpha_s}$ in Shapiro and Walker (2018). Shapiro and Walker estimate the elasticities by running a 2SLS regression of changes in emission intensity (at the county-industry level) on changes in abatement costs, instrumenting the latter with changes in attainment status. This yields a unique elasticity for every pollutant. They then obtain industry-specific values by scaling this elasticity with industry-level abatement costs. As their data is limited to manufacturing, they do not have an estimate for utilities. The utility sector being the largest emitter of fine particles, we set its elasticity to equal the one of the most polluting manufacturing industry, Primary Metals.

that in our model, λ_n^j corresponds to the fraction of time that workers spend in production. Thus, from a firm's perspective, increases in abatement (which reduce this fraction) are effectively a negative productivity shock.

Table 4: Estimated productivity effects of the EPA's fine particle regulations

Industry	Implied productivity change
Utilities	-10.8%
Paper products	-5.9%
Non-metallic mineral products	-7.7%
Primary metals	-10.8%

Notes: The table shows the percentage changes in industry-level productivity due to our estimated changes in abatement costs (computed as $\widehat{\lambda}_n^j - 1$). These changes only apply in non-attainment commuting zones.

Table 4 shows that abatement shocks are sizeable, ranging between a 6% and a 11% reduction in productivity. Shapiro and Walker's estimates for abatement elasticities are relatively large (ranging around 20 for polluting industries), explaining that our estimates of a large fall in emission intensity translate into more moderate changes in productivity. Note also that by construction, all industry-level variation in these shocks is due to variation in abatement elasticities.

5.2 Characteristics of the pre-reform equilibrium

To compute the equilibrium in relative changes, we need to know a number of characteristics of the pre-reform equilibrium: the distribution of the labour force M_n^j, trade shares π_{in}^j and incomes $w_n L_n$ (which together imply sales sales s_{ni}^j), industry spending shares α^j, and the initial distribution of emissions E_n^j.[26] To compute these figures, we rely on the data introduced in Section 2, combined with some additional sources. All are described in greater detail in Appendix A.

For computational reasons, we do not include all 741 commuting zones and 60 industries in the model. Instead, we focus on the 100 commuting zones with the highest income, aggregating all others into a "Rest of the US" commuting zone (so that $N = 101$). Likewise, we aggregate all non-manufacturing industries, with the exception of utilities and mining, to a generic "non-manufacturing" industry. This implies $J = 21$.

We set the initial spending of each commuting zone n in the model to equal the commuting zone's total personal income, taken from the BEA. We set industry spending

[26]Equation (21) shows that we also need the distribution of physical output flows, $\tilde{s}_{ni}^j$. As we do not have data on physical output, we compute $\tilde{s}_{ni}^j$ analogously to s_{ni}^j, adjusting for state-level differences in prices.

shares α_j to equal industry shares in total value added, computed with the real value added data described in Section 2. Moreover, we use data from the Census Bureau's Commodity Flow Survey (CFS) to compute the trade shares π^j_{ni}. As the CFS does not have data for utilities and for our generic non-manufacturing industry, we assume that these industries are not traded (implying $\pi^j_{nn} = 1$). Putting together these elements, we can compute the implied relative incomes and sales shares.

Finally, using our data from Section 2, we compute initial emission shares for each commuting zone-industry. To obtain the initial distribution of the labour force, we use data from the Census to estimate the number of unemployed workers in each commuting zone-industry pair. We then compute the labour force as the sum of employed and unemployed workers, using our employment data from Section 2.[27]

5.3 Elasticities

Finally, we need to calibrate five sets of key elasticities: the trade elasticities θ^j for every industry j, the inverse migration elasticity κ, the inverse industry switching elasticity ν, the inverse labour supply elasticity ζ, and the strength of the pollution externality, captured by the elasticity of productivity to pollution, ψ.

We set trade elasticities to $\theta^j = 5$ for every industry j, a standard value in the trade literature (Costinot and Rodríguez-Clare, 2014). Following Rodríguez-Clare *et al.* (2020), we set the industry and commuting zone switching elasticities to $\nu = 0.55$ and $\kappa = 12.3$.[28]

We set the two remaining elasticities internally, in order to replicate two key results from our triple difference employment regressions. We focus on our baseline results (shown in column (2) of Table 1), which compare employment growth in non-attainment and attainment commuting zones after the reform, for both clean and polluting industries. We run the same regression with data generated by our model, and choose the emission externality ψ and the inverse labour supply elasticity ζ in order to match the empirical coefficients. Precisely, we estimate

$$\ln \widehat{L^j_n} = \gamma_1^{\text{Model}} \cdot \mathbb{1}^{\text{NA}}_n + \gamma_2^{\text{Model}} \cdot \left(\mathbb{1}^{\text{NA}}_n \cdot \text{Emit}^j_{1999}\right) + \alpha^j + \epsilon^j_n, \tag{25}$$

which is the exact one-period equivalent of the specification in column (2) of Table 1.[29]

[27] Some commuting zone-industry pairs have no employment or output. This is inconsistent with the model. For all these cases, we replace employment or output with a very small number (1e-5).

[28] Rodríguez-Clare *et al.* (2020) estimate these numbers by matching the estimates of Autor *et al.* (2013) for the impact of Chinese import competition across commuting zones.

[29] As Table 1 considers yearly growth rates, we multiply its estimates by 14 (our time horizon in the quantitative analysis) to obtain the values for our model targets. We estimate model regressions by WLS,

Intuitively, the relative employment growth of clean industries (captured by γ_1^{Model}) helps us to identify the emission externality. With a strong externality, clean industries in non-attainment commuting zones see their productivity increase when emissions fall. This increases their real wage and employment relative to clean industries in attainment commuting zones. On the other hand, with a weak externality, clean industries in non-attainment commuting zones perform worse: the productivity losses of polluting industries decrease real wages and employment, and due to a home bias in consumption, this affects local clean industries the most. This intuition is formalized by the left panel of Figure 6, which plots the obtained values for γ_1^{Model} against different values of ψ. For each value of ψ, we randomly vary the value of the labour supply elasticity ζ. The black dots show the median value of the model regression coefficient, and the grey dots the 25th and 75th percentiles. There is a clear positive relation between the regression coefficient and the emission externality, validating our identification intuition.

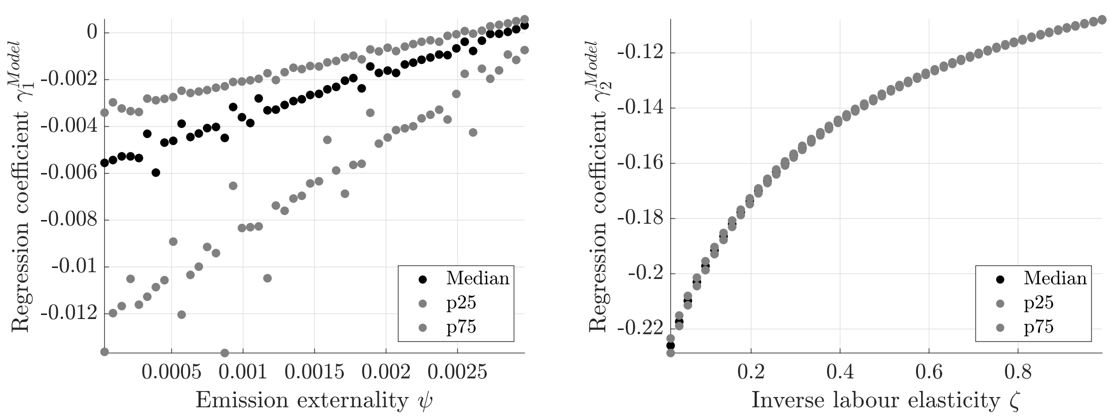


Figure 6: Identification of the elasticity parameters

The second regression coefficient, γ_2^{Model}, captures the differential response of polluting industries. This coefficient identifies the labor supply elasticity. As polluting industries in non-attainment commuting zones receive a direct negative productivity shock, the coefficient is always negative (even with a strong emission externality, the relative productivity of polluting industries with respect to clean ones must decline). The labour supply elasticity governs how strongly employment responds to a lower real wage, and thus governs the scale of this coefficient. This is shown in the right panel of Figure 6: the coefficient γ_2^{Model} strongly increases in the inverse labour supply elasticity ζ, and is virtually independent of the emission externality. Indeed, as the emission externality applies equally to all industries, it cannot explain any differential effect for polluting industries.

Proceeding in this way, we match both regression coefficients exactly, and obtain

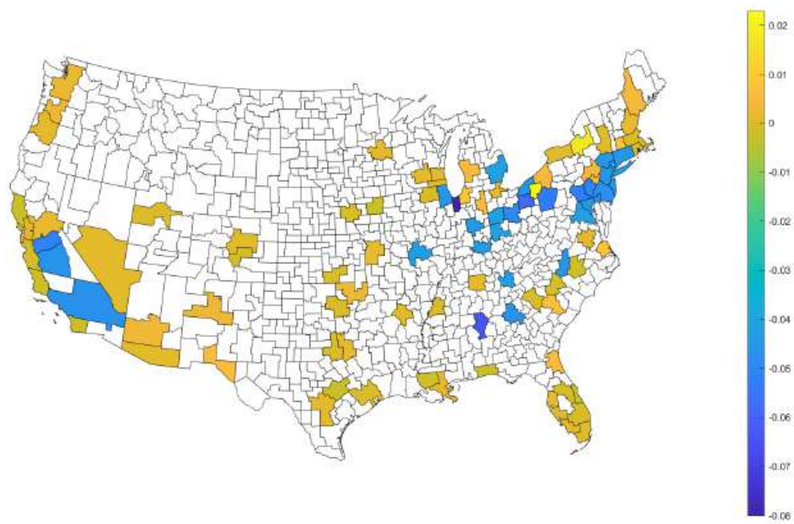
weighting observations by initial employment.

elasticities of $\psi = 1.8 \cdot 10^{-4}$ and $\zeta = 0.07$. The emission elasticity implies that a reduction of emissions by 1 log point (63%) increases overall productivity by 0.018%, a modest increase. Our inverse labour supply elasticity is somewhat lower than in Acemoglu and Restrepo (2020), who find $\zeta = 0.17$, implying a relatively elastic labour supply.

6 Quantitative analysis

6.1 Baseline results

Commuting zone effects We are now ready to consider the effects of fine particle regulations in our calibrated model. Figure 7 illustrates changes in commuting zone employment triggered by the reform. On average, non-attainment commuting zones lost employment, while most attainment commuting zones made small gains.



Notes: This figure illustrates changes in commuting zone employment as a result of EPA fine particle regulations. Our analysis focuses on the 100 commuting zones with the highest aggregate income. Commuting zones which are not shaded in this map are aggregated into a "rest of the US" commuting zone.

Figure 7: The local employment impact of fine particle regulations

The employment losses of non-attainment commuting zones are due to changes in productivity: there was a direct negative effect of fine particle regulations on the productivity of polluting industries (as shown in Table 4), and the positive externality of lower emissions was not strong enough to overturn this. This decline in productivity lowered real wages, leading to out-migration and lower labour supply. Nevertheless, there are interesting differences among non-attainment commuting zones, with employment losses ranging between 4.0% for New York and 7.7% for Gary (IN). These differences can be explained by commuting zone specialization. In New York, fine particle emissions are concentrated in the utility industry, which is not traded. Thus, when the productivity of this industry fell and its price rose, local consumers could not substitute away from it, and this sustained demand. In Gary, on the other hand, fine particle emissions mostly come from tradable manufacturing industries, such as primary metals. When regulation increased the prices of these products, consumers across the country could substitute away from Gary and switch to other suppliers, explaining substantially higher employment losses.

Within attainment commuting zones, outcomes range between a fall of 0.3% in employment in Palm Bay (FL) and an increase of 2.3% in Youngstown (OH). Youngstown's employment gains were the mirror image of Gary's losses, since Youngstown is specialized in tradable polluting industries and thus gained from the reallocation of trade flows.

Aggregate effects Table 5 summarizes our main results for aggregate outcomes and for the 10 largest commuting zones. Our model indicates that the introduction of fine particle regulations lowered aggregate emissions by 12.9%. In the data, total fine particle emissions fell by 57% over the 14 years after the reform: thus, the model suggests that the EPA regulations accounted for roughly one quarter of all emission reductions.

Table 5: Changes in economic outcomes due to EPA regulations

	Emissions	GDP	GDP/Worker	Employment	Man. empl.
United States	-12.9%	-1.61%	-0.06%	-1.55%	-1.63%
Los Angeles	-41%	-5.03%	-0.45%	-4.6%	-4.07%
New York	-68.3%	-4.35%	-0.33%	-4.03%	-3.66%
Chicago	-41.2%	-4.72%	-0.32%	-4.41%	-4.42%
Newark	-59.9%	-4.73%	-0.36%	-4.39%	-4.16%
San Francisco	-0.1%	0.23%	0.04%	0.19%	-0.18%
Boston	0.2%	0.03%	0.03%	-0.01%	-0.31%
Philadelphia	-50.2%	-4.99%	-0.36%	-4.65%	-4.52%
Detroit	-67.2%	-4.43%	-0.33%	-4.11%	-3.98%
Washington DC	-81.6%	-4.45%	-0.32%	-4.14%	-3.61%
Houston	-0.3%	0.01%	0.01%	0.01%	-0.12%

Notes: This table shows the predictions of our calibrated model for the change in outcomes between the pre and post-reform equilibrium.

However, Table 5 also shows that the regulations had an economic cost: our model suggests that they lowered aggregate employment by 1.55% (corresponding to 1.36 million jobs). They also lowered GDP per worker by 0.06%.

Importantly, the aggregate employment loss implied by the model is about 15% lower than the relative difference between attainment and non-attainment commuting zones implied by our employment regressions (which, as we showed in Section 3, amounted to 1.6 million jobs). This is due to the spillover effects of the reform on attainment commuting zones (the control group in the regressions). In the model, attainment commuting zones experienced on average a 1% increase in employment, and this somewhat dampened the aggregate employment loss.

The positive effect of the reform on employment in attainment commuting zones is due to general equilibrium forces. In our model, various general equilibrium forces are at play, some creating positive spillovers, and others negative ones. Positive spillovers include the reallocation of activity in tradable industries (as in the previously discussed case of Gary and Youngstown), raising wages and therefore employment in some attainment commuting zones. They also include a reallocation of the labour force through migration from non-attainment to attainment commuting zones, as a result of changes in real wages. However, there are also negative spillovers. Most notably, lower productivity of tradable polluting industries in non-attainment commuting zones increases prices, and thus, all else equal, lowers real wages and labour supply in all commuting zones. Our results imply that in the calibrated model, positive spillovers turn out to be quantitatively larger than negative ones. Therefore, the aggregate economic costs of the regulation were smaller than the relative costs implied by our regression evidence.

Industry-level effects Finally, Table 6 summarizes industry-level outcomes. The first column shows the overall productivity change of industries after the reform (computing an employment-weighted average of productivity changes across commuting zones), while the second shows the change in total employment.

Obviously, polluting industries experience greater productivity losses than clean ones (which experience in general a very small productivity gain due to the externality). However, while polluting industries do have on average higher employment losses than clean ones, the difference does not appear to be large. The reason for this is that the regulation does not affect polluting industries in general, but only polluting industries in non-attainment commuting zones. Thus, polluting industries in attainment commuting zones gain employment, dampening the overall loss. Clean industries, in turn, experience employment losses due to the negative general equilibrium spillovers described above: regulation lowers real wages, and this depresses labour supply even for industries which do not experience a fall in productivity.

Table 6: Industry-level changes

	Productivity	Employment
Mining, except oil and gas	0%	-0.85%
Utilities	-3.68%	-1.55%
Food and beverage and tobacco products	0%	-1.3%
Textile mills and textile product mills	0%	-1.39%
Apparel and leather and allied products	0.01%	-2%
Wood products	0%	-0.61%
Paper products	-2.16%	-2.08%
Printing and related support activities	0.01%	-1.71%
Petroleum and coal products	0.01%	-1.6%
Chemical products	0.01%	-1.77%
Plastics and rubber products	0.01%	-1.55%
Nonmetallic mineral products	-2.2%	-0.78%
Primary metals	-4.9%	-4.43%
Fabricated metal products	0.01%	-1.82%
Machinery	0.01%	-1.43%
Computer and electronic products	0%	-1.38%
Electrical equipment, appliances, and components	0.01%	-1.73%
Transportation equipment	0.01%	-1.83%
Furniture and related products	0%	-1.39%
Miscellaneous manufacturing	0.01%	-1.63%
Other Non-Manufacturing	0.01%	-1.54%

Notes: This table shows the predictions of our calibrated model for industry-level changes between the pre and post-reform equilibrium.

6.2 Robustness checks

Shutting down migration To better understand the drivers of our results, we consider two robustness checks. First, we analyse outcomes in the absence of migration across commuting zones (setting the inverse migration elasticity to $\kappa = 100$, and re-computing our model's predictions for all outcomes). All other parameters are the same as in the baseline.

Table 7 shows the impact of the reform without migration. While aggregate effects are roughly the same as in the baseline, there are now less spillovers across space: attainment commuting zones gain less employment (e.g., San Francisco's employment increases by 0.06% rather than 0.19% in the baseline) and non-attainment commuting zones lose less (e.g. employment in Los Angeles falls by 4.4% rather than 4.6%). Nevertheless, there are still spillovers even without migration, due to the trade channel.

Table 7: Changes in economic outcomes without migration

	Emissions	GDP	GDP/Worker	Employment	Man. empl.
United States	-13%	-1.62%	-0.07%	-1.56%	-1.64%
Los Angeles	-40.9%	-4.82%	-0.45%	-4.39%	-3.86%
New York	-68.3%	-4.18%	-0.33%	-3.86%	-3.49%
Chicago	-41.2%	-4.52%	-0.32%	-4.21%	-4.23%
Newark	-59.9%	-4.54%	-0.36%	-4.19%	-3.97%
San Francisco	-0.1%	0.1%	0.04%	0.06%	-0.31%
Boston	0.1%	-0.09%	0.03%	-0.12%	-0.42%
Philadelphia	-50.1%	-4.78%	-0.36%	-4.44%	-4.3%
Detroit	-67.1%	-4.26%	-0.33%	-3.94%	-3.81%
Washington DC	-81.6%	-4.28%	-0.32%	-3.97%	-3.44%
Houston	-0.4%	-0.1%	0.01%	-0.1%	-0.23%

Notes: This table shows the predictions of our calibrated model for the change in outcomes between the pre and post-reform equilibrium. For this table, we set the inverse migration elasticity κ to 100.

The role of the emission externality Finally, we investigate the role of the emission externality ψ, by recomputing our model's predictions when setting this parameter to 0. All other parameters are the same as in the baseline.

Table 8: Changes in economic outcomes without migration

	Emissions	GDP	GDP/Worker	Employment	Man. empl.
United States	-12.9%	-1.69%	-0.07%	-1.63%	-1.7%
Los Angeles	-41.1%	-5.15%	-0.46%	-4.72%	-4.19%
New York	-68.4%	-4.64%	-0.35%	-4.3%	-3.93%
Chicago	-41.3%	-4.85%	-0.33%	-4.53%	-4.55%
Newark	-60%	-4.96%	-0.37%	-4.6%	-4.37%
San Francisco	-0.1%	0.24%	0.04%	0.19%	-0.17%
Boston	0.2%	0.03%	0.03%	0%	-0.3%
Philadelphia	-50.2%	-5.16%	-0.37%	-4.81%	-4.68%
Detroit	-67.3%	-4.71%	-0.35%	-4.38%	-4.25%
Washington DC	-81.7%	-4.88%	-0.35%	-4.55%	-4.02%
Houston	-0.3%	0.02%	0%	0.01%	-0.11%

Notes: This table shows the predictions of our calibrated model for the change in outcomes between the pre and post-reform equilibrium. For this table, we set the emission externality ψ to 0.

Table 8 shows that positive externalities from lower emissions have limited employment losses somewhat: without them, aggregate employment would have fallen by 1.63%, rather than by 1.55% as in the baseline.

7 Conclusions

In this paper, we have developed a quantitative model, disciplined by extensive empirical evidence, to estimate the effect of fine particle regulations introduced by the EPA in the early 2000s. We found that the regulations substantially lowered fine particle emissions, but also led to a 1.55% drop in employment.

We do not attempt to quantify the health benefits of lower emissions. Nevertheless, our results do provide some suggestive evidence for a cost-benefit analysis. Indeed, prior research comparing estimated health benefits with relative employment losses across commuting zones has concluded that the benefits of air pollution regulation substantially exceed its costs (see Currie and Walker, 2019). However, our analysis suggests that regulations tend to have positive spillover effects on non-regulated areas, so that aggregate employment losses are lower than relative changes in employment. Thus, our findings could be interpreted as further reinforcing the claim that the benefits of Clean Air Act regulations have outweighed their costs.

Finally, while our paper has focused on fine particle regulations in the United States, its methods can easily be applied to other episodes, shedding more light on the benefits and costs of environmental regulations. Given the scale of the Green Transition faced by the world economy, these issues are likely to be of ever greater interest to public debate and policy makers.

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A Data Appendix

A.1 Commuting zone attainment status

The EPA reports county attainment status for different pollutants in its Green Book.[30] For counties exceeding the NAAQS thresholds, the EPA distinguishes cases in which the whole county is in non-attainment status, and cases in which only a part of a county is in non-attainment status.

We map these county-level observations to commuting zones using a correspondence table created by Autor and Dorn (2013).[31] In our baseline analysis, we assume that a commuting zone is in non-attainment status if at least one third of its population lives in a county which is either wholly or partially in non-attainment status, as in Vona *et al.* (2019). We obtain county-level population data (for the year 2017) from the Census Bureau.[32]

A.2 Air pollution emissions

Our data for fine particle emissions comes from the EPA's National Emissions Inventory (NEI).[33] The NEI contains information on emissions at the facility level. Emissions for most facilities are not directly observed by the EPA, but computed by the agency based on emission factors.[34] We aggregate emissions to the county-level by taking the sum across all facilities.

Different years of the NEI data use different industry classifications. Until 2001, the NEI uses the Standard Industrial Classification (SIC), and from 2002 onward, 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 2002 codes, using several publicly available industry concordance files. To convert 3-digit SIC 1987 codes into 3-digit NAICS 2002, we use the crosswalk developed by Foster *et al.* (2016), which provides

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

[31] The correspondence can be downloaded at https://www.ddorn.net/data.htm#Local%20Labor%20Market%20Geography.

[32] The county population data can be downloaded at https://www.census.gov/data/datasets/time-series/demo/popest/2010s-counties-total.html#par_textimage_70769902.

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

[34] 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 follows: $E = A \cdot EF \cdot (1 - ER/100)$, 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.

employment weights.[35] To convert different NAICS vintages into NAICS 2002 codes, we instead rely on the Industry Bridge Statistics files provided by the Census, which also include employment weights.[36]

After converting all data to 3-digit NAICS 2002 codes, we aggregate them slightly further, in order to be consistent with the BEA industry classification (which we use to get data on value added, and therefore emission intensities). This results in 60 industries which we use for all our empirical analysis, listed in Table A.1.

Table A.1: Industries included in the empirical analysis

Industry	NAICS Code(s)
Forestry, fishing, and related activities	113-115
Oil and gas extraction	211
Mining, except oil and gas	212
Support activities for mining	213
Utilities	221
Construction	236-238
Food and beverage and tobacco products	311-312
Textile mills and textile product mills	313-314
Apparel and leather and allied products	315-316
Wood products	321
Paper products	322
Printing and related support activities	323
Petroleum and coal products	324
Chemical products	325
Plastics and rubber products	326
Nonmetallic mineral products	327
Primary metals	331
Fabricated metal products	332
Machinery	333
Computer and electronic products	334
Electrical equipment, appliances, and components	335
Transportation equipment	336
Furniture and related products	337
Miscellaneous manufacturing	339
Wholesale trade	423-425
Motor vehicle and parts dealers	441
Other retail	442-444, 446-448, 451, 453-454
Food and beverage stores	445

[35]For industries that are missing in this crosswalk, we instead rely on the standard Census concordance file, available at https://www.census.gov/eos/www/naics/concordances/concordances.html.

[36]These bridge files can be downloaded at https://www.census.gov/data/tables/2002/econ/census/core-business-statistics-series.html.

Industry	NAICS Code(s)
General merchandise stores	452
Air transportation	481
Rail transportation	482
Water transportation	483
Truck transportation	484
Transit and ground passenger transportation	485
Pipeline transportation	486
Other transportation and support activities	487-488, 492
Warehousing and storage	493
Publishing industries, except internet (includes software)	511
Motion picture and sound recording industries	512
Other information services	515-519
Federal Reserve banks, credit intermediation, and related activities	521-522
Securities, commodity contracts, and investments	523
Insurance carriers and related activities	524
Funds, trusts, and other financial vehicles	525
Real estate	531
Rental and leasing services and lessors of intangible assets	532-533
Professional, scientific, and technical services	541
Management of companies and enterprises	551
Administrative and support services	561
Waste management and remediation services	562
Educational services	611
Ambulatory health care services	621
Hospitals	622
Nursing and residential care facilities	623
Social assistance	624
Performing arts, spectator sports, museums, and related activities	711-712
Amusements, gambling, and recreation industries	713
Accommodation	721
Food services and drinking places	722
Other services, except government	811-813

Finally, we aggregate county-level emissions data to the commuting zone level, using again the correspondence of Autor and Dorn (2013). It is also worth noting that for our quantitative analysis, we aggregate all non-manufacturing industries (with the exception of Mining and Utilities) into a single industry.

A.3 Employment, labour force, income and value added

We use data on employment for every year between 1999 and 2019 from the County Business Patterns (CBP).[37] The raw data contains information on industry employment (at various levels of aggregation) for each county. Different years use different vintages of the NAICS classification, so we convert all data into NAICS 2002 3-digit codes, using the same crosswalks as in Section A.2.[38] We then aggregate county data to the commuting zone level, using once more the Autor and Dorn (2013) crosswalk.

To obtain a measure of the commuting zone-industry labour force (needed for the calibration of our model), we combine this data with data on unemployed workers. We obtain the total number of unemployed workers in every county from the BLS Local Area Unemployment Statistics (LAUS).[39] Then, we split this total number across industries using commuting zone-specific weights obtained using Census data from IPUMS.[40] Precisely, the Census records for each unemployed person the industry in which the person last worked, and we use that information to construct the weights.

To measure aggregate income for commuting zones, we use data on personal income from the BEA.[41] Finally, we also use data on real value added at the industry level from the BEA.[42] To compute emission intensity at the commuting zone-industry level, we construct a proxy for value added at that level by splitting up industry-level data using our employment weights.

A.4 Trade between commuting zones

To measure trade flows between commuting zones, we rely on the Census Bureau's Commodity Flow Survey (CFS) for the year 1997.[43] This database contains the value of shipments of different goods between states and Metropolitan Statistical Areas (MSAs). Goods are classified according to the Standard Classification of Transported Goods (SCTG), which we convert into NAICS 3-digit codes.

Note that the data covers only manufacturing industries and mining. We assume that

[37] The data can be downloaded at https://www.census.gov/programs-surveys/cbp.html.

[38] In some industries and some years, employment data is missing due to disclosure reasons. Whenever employment data is available both before and after such an instance, we linearly interpolate the missing years.

[39] Data can be downloaded at https://www.bls.gov/lau/tables.htm.

[40] The data can be downloaded at https://usa.ipums.org/usa/

[41] The data can be downloaded at https://www.bea.gov/data/income-saving/personal-income-county-metro-and-other-areas.

[42] The data can be downloaded at https://apps.bea.gov/iTable/iTable.cfm?isuri=1&reqid=151&step=1%20https://apps.bea.gov/industry/Release/XLS/GDPxInd/ValueAdded.xlsx

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

the other two industries in our quantitative model (utilities and non-manufacturing) are not traded. That is, that in these industries, 100% of the shipments of any commuting zone n remain in commuting zone n.

For all other industries, we construct shipments between commuting zones by splitting up shipments between states, using commuting zone population shares. To account for the fact that trade within commuting zones is more prevalent than trade between commuting zones, we adjust these flows by applying a correction based on the own-trade share of all MSAs in the data.

B Model details

B.1 Equilibrium conditions in levels

B.1.1 Labour supply and location choices

The worker household's problem, summarized in equation (5), implies that that each household locating in commuting zone n and industry j supplies $\left(w_n^j/P_n\right)^{1/\zeta}$ units of labour. Denoting by M_n^j the mass of workers in commuting zone n and industry j, commuting zone-industry labour supply is

$$L_n^j = M_n^j \left(\frac{w_n^j}{P_n}\right)^{1/\zeta}. \tag{A.1}$$

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

$$\iota_n^j + \eta_{n,h}^j + \ln\left(\frac{\zeta}{1+\zeta}\right) + \frac{1+\zeta}{\zeta}\ln\left(\frac{w_n^j}{P_n}\right).$$

Each worker 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

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

where $u_n^j \equiv \iota_n^j + \frac{1+\zeta}{\zeta}\ln\left(\frac{w_n^j}{P_n}\right)$ 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 (6). This probability also equals the mass of workers choosing commuting zone-industry (n,j).

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

$$M_n^j = \int_{-\infty}^{+\infty} \mathbb{P}\left(\max_{(i,s)\neq(n,j)} \left(u_i^s + \eta_i^s\right) \ \leq u_n^j + \eta_n^j \mid u_n^j + \eta_n^j = x \right) \ g_n^j(x)\, dx,$$

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

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

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,

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

Simplifying this expression, we obtain

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

with

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

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

$$M_n^j = \frac{\left(\sum_{s=1}^{J}\exp\left(\frac{u_n^s}{\nu}\right)\right)^{\frac{\nu}{\kappa}}}{\sum_{i=1}^{N}\left(\sum_{s=1}^{J}\exp\left(\frac{u_i^s}{\nu}\right)\right)^{\frac{\nu}{\kappa}}} \frac{\exp\left(\frac{u_n^j}{\nu}\right)}{\sum_{s=1}^{J}\exp\left(\frac{u_n^s}{\nu}\right)}.$$

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

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

The distribution of workers within a commuting zone depends on relative nominal wages and amenities across industries. Note that real wages do not appear here, as all workers within a commuting zone face the same price index.

Finally, the distribution of workers across commuting zones holds

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

The total mass of workers in a commuting zone depends on the relative real wage and the relative amenities of that commuting zone.

B.1.2 Trade shares and price indices

As equation (9) shows, both aggregate emissions and abatement shift the productivity distribution in a given commuting zone-industry pair. As these shifts are identical across firms, it is straightforward to show that 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 can solve for all endogenous outcomes by using standard techniques from Ricardian trade models in the Eaton and Kortum (2002) tradition. We denote by π_{ni}^j the share of expenditure of commuting zone n in industry j that is spent on goods of commuting zone i. This share is given by

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

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, in turn, depends on productivity, wages and trade costs. The industry-level price index is

$$P_n^j = A^j \left(\sum_{i=1}^{N} T_i^j \left(w_i^j d_{ni}^j \right)^{-\theta^j} \right)^{-\frac{1}{\theta^j}}, \tag{A.7}$$

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

$$P_n = \prod_{j=1}^{J} \left(\frac{P_n^j}{\alpha^j} \right)^{\alpha^j}. \tag{A.8}$$

Equations (A.3) to (A.8) define labour force shares, trade shares and prices as a function of productivity and nominal wages. To close the model, we need to introduce two more relationships. First, we note that for every commuting zone n and industry j, the nominal income of workers is equal to total spending on the goods that they produce. Therefore,

$$w_n^j L_n^j = \alpha^j \sum_{i=1}^{N} \pi_{in}^j \left(1 + \chi_i\right) w_i L_i. \tag{A.9}$$

Finally, we need to take into account that productivity is not exogenous, but depends on endogenous emissions due to the externality. The next section derives these emissions.

B.1.3 Commuting zone-level emissions

To start, we compute total emissions for a commuting zone-industry pair (n, j), denoted by E_n^j. From equation (10), we get

$$E_n^j = \int_0^1 e_n^j(\omega)\, d\omega = \sigma_n^j \left(\lambda_n^j \right)^{\beta^j} \int_0^1 y_n^j(\omega)\, d\omega. \tag{A.10}$$

To evaluate the interval in equation (A.10), we split up the total production of 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

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

where Ω_{in}^j stands for the set of 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 consumption: for every unit being consumed in commuting zone i, d_{in}^j units have to be produced in commuting zone n.

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

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

Replacing this expression into the previous integral, we get

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

To evaluate the above integral, we use two results from Eaton and Kortum (2002). First, the mass of 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 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 $\Phi_i^j = \sum_{n=1}^N T_n^j\left(w_n^j d_{in}^j\right)^{-\theta^j}$. 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

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

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

$$E_n^j = B^j \sigma_n^j \left(\lambda_n^j\right)^{\beta^j} \sum_{i=1}^{N} d_{in}^j \pi_{in}^j Y_i^j. \tag{A.11}$$

Noting that by definition, the ideal price index holds $P_i^j Y_i^j = \alpha^j \left(1 + \chi_i\right) w_i L_i$, and summing up emissions across industries finally gives

$$E_n = \sum_{j=1}^{J} \left(\alpha^j B^j \sigma_n^j \left(\lambda_n^j\right)^{\beta^j} \left(\sum_{i=1}^{N} d_{in}^j \pi_{in}^j \frac{\left(1 + \chi_i\right) w_i L_i}{P_i^j} \right) \right). \tag{A.12}$$

B.2 Equilibrium conditions in relative changes and solution algorithm

The equilibrium conditions in relative changes can be obtained from the equilibrium conditions in levels through straightforward algebra. In particular, note that the change in total emissions holds

$$\widehat{E}_n = \sum_{j=1}^{J} \frac{E_n^j}{E_n} \cdot \widehat{E}_n^j,$$

which gives equation (21) in the main text.

Using the equilibrium conditions in relative changes, we can solve the model using a simple algorithm.

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

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

   (a) We compute the matrix of changes in productivity $\widehat{T}_n^j$, using equation (15).

   (b) Then, we solve the equation system defined by (19) to obtain changes in nominal wages (normalizing $\widehat{w}_1^1 = 1$, and using the fact that all other endogenous variables appearing in these equations are pinned down by changes in productivity and nominal wages).

(c) From this, we deduce the implied change in emissions, using equation (21).

3. If the largest difference between our guess for emission changes and implied emission changes is lower than 0.001%, we consider that the solution algorithm has converged. Otherwise, we update our guess for emission changes according to

$$\widehat{E}_n^{(iter+1)} = 0.75 \cdot \widehat{E}_n^{\text{implied}} + 0.25 \cdot \widehat{E}_n^{(iter)}.$$

   and return to Step 2 (a).