Deep Industrial Decarbonization: Theory and Evidence from South Korea*

Costas Arkolakis Yale University Cheolhwan Kim Yale University

Emmanuel Murray Leclair University of Chicago

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Abstract

We examine deep industrial decarbonization using new theory and empirical evidence from South Korea. South Korea has instituted a series of national and region-specific regulations with the aim to curb industrial emissions. For heavy industry, such as steel and cement, this requires significant technological upgrades with important fixed costs. Drawing on establishment-level data from the Statistical Business Registers and the Mining and Manufacturing Survey, we document a dramatic rise in electrification: between 2016 and 2022, the share of plants relying solely on electricity almost doubled (from 35% to 60%). Despite wide variation in local regulations, we find limited evidence of carbon leakage in the form of output reallocation. More regulated, urban districts exhibit stronger adoption of cleaner fuels and even faster output growth, consistent with these areas having higher ability to transition out of fossil fuels.. We develop and estimate a rich dynamic spatial general equilibrium model where firms pay switching costs to adopt or drop fuels, and where region-specific regulations affect local fuel prices. The model highlights how some regions could transition quickly and remain competitive at the expense of other regions. While not necessarily efficient in a first-best sense, Korea's uneven regulatory landscape may have moderated disparities in economic activity across regions.

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1 Introduction

South Korea has seen a striking shift toward cleaner energy sources in its mining and manufacturing sector, driven in part by a series of national and regional decarbonization policies introduced over the past decade. Using micro-level data from the Statistical Business Registers (SBR) and the Mining and Manufacturing Survey (MMS), we find that the share of mining and manufacturing plants relying solely on electricity more than doubled—from roughly 35% to 65%—over the 2016 to 2022 period. A decomposition of greenhouse gas emissions reveals that this massive transition at the plant level has played a critical role in countering emissions increases from industry-wide economic growth. Thus, even as the Korean mining and manufacturing sector has continued to expand, overall emissions intensities have declined.

A key feature of Korea's decarbonization efforts is the substantial variation in local environmental policies across districts. For instance, some regulations restrict the use of specific fossil fuels. Other regulations restrict the use of specific mining or manufacturing processes, while others impose a nation-wide cap-and-trade system for greenhouse gas emissions. Some districts, typically in more rural areas, only face one or two regulations while other district (typically in large urban areas) face all of them. We observe that these policy differences across districts do not seem to cause "carbon leakage" through the reallocation of economic activity across regions—e.g., the notion that stricter regulation in certain regions would suppress local output, pushing output toward areas with more lenient regulations. Instead, more regulated, often urban districts exhibit not only greater adoption of cleaner fuels but also higher output growth. This pattern suggests that firms in these regions may be better able to switch out of fossil fuels—perhaps because of higher baseline productivity or superior access to cleaner technologies—thereby remaining competitive despite tougher regulation.

Motivated by these empirical findings, we develop a dynamic spatial general equilibrium model that features endogenous, discrete choices of fuel sets and incorporates region-specific environmental regulations. In the model, firms pay fixed costs to drop or adopt fuels, and they face local differences in effective fuel prices due to local regulations. These policy-induced changes then propagate through input costs and general equilibrium wages, affecting the pace of their green transition and the distribution of economic activity across regions. Crucially, we characterize a novel "dynamic inter-fuel elasticity of substitution" that can vary across regions, whereby more productive and well-resourced regions can adapt more quickly to high fuel prices without suffering as large a reduction in output. Absent these differential capabilities across regions, one would expect regions with stricter regulation to lose competitiveness, but the data show otherwise. Our analysis raises the possibility that

South Korea's uneven regulatory landscape may have helped mitigate carbon leakage and moderated disparities in economic activity across regions, potentially improving welfare—not necessarily in an efficiency sense, but from the perspective of a planner who cares about inequalities in economic activity. By quantitatively examining these dynamics, we shed light on how spatially differentiated environmental policies can shape the industrial geography of an economy transitioning toward cleaner energy.

Literature We build on three strands of literature, bridging the gap between two bodies of literature environmental policies and the spatial economics literature. The first literature examines how environmental policies influence abatement and clean innovation decisions. Going back to the work of Copeland and Taylor (2004), pollution abatement has been analyzed through the installation of filters and scrubbers to limit local air pollution (Greenstone, Pande, Sudarshan, and Ryan, 2025), investments in energy efficiency (Hawkins-Pierot and Wagner, 2022; Christensen, Francisco, and Myers, 2022), and substitution from dirty to clean fuels (Murray Leclair, 2024; Alpino, Citino, and Frigo, 2023; Ahmadi and Yamazaki, 2020; Andersson, 2019). Clean innovation is generally studied with patents dynamics.. For instance, Aghion, Dechezleprêtre, Hémous, Martin, and Reenen (2016) distinguish dirty and clean patents in auto industry innovation. However, these papers typically focus on a closed economy, ignoring the possibility of carbon leakage across regions and countries in the short run. Carbon leakage refers to the case where spatially differentiated environmental regulation causes a shift of dirty production and emissions from more regulated to less regulated regions. Carbon leakage can take the form of explicit relocation of production by firms or implicitly through equilibrium mechanisms that make unregulated firms relatively more competitive (Tanaka, Teshima, and Verhoogen, 2022; Chen, Chen, Liu, Serrato, and Xu, 2021; Yang, Lin, Wang, and Peng, 2024). However, the carbon leakage literature typically abstract from abatement and clean innovation, an outcome that is likely to realize in the long run.

We combine insights from both literatures by studying how the heterogeneous responses of firms to national and environmental policies—both in the short and the long run—can be associated with a reallocation of economic activity across regions. One of our key contribution is to show that emissions do not necessarily leak from more to less heavily regulated regions. Indeed, the reallocation of economic activity crucially depends on the ability of firms in different regions to abate emissions. It is entirely possible that economic activity reallocates towards more heavily regulated regions. In the Korean context, we find that urban and richer regions face more stringent regulation but also become more competitive. This motivates the addition of space in the analysis, allowing us to better understand the spatial variation in abatement decisions and emissions leakage (or lack thereof), and to study the welfare

implications of spatially differentiated policies.

This is where the third literature comes in. This growing literature studies economic and environmental outcomes in space in response to global or local variations in environmental polices or climate shocks (Golosov, Hassler, Krusell, and Tsyvinsky, 2014; Desmet and Rossi-Hansberg, 2015; J. S. Shapiro and Walker, 2018; Conte, Desmet, Nagy, and Rossi-Hansberg, 2021; Jose-Luis Cruz, 2024; Farrokhi and Lashkaripour, 2022; Kortum and Weisbach, 2021; José-Luis Cruz and Rossi-Hansberg, 2022; José-Luis Cruz and Rossi-Hansberg, 2024; Krusell and Smith, 2022; Arkolakis and Walsh, 2023; Desmet and Rossi-Hansberg, 2024; Weisbach, Kortum, Wang, and Yao, 2023). This paper complements this literature by focusing on a dynamic abatement mechanism: changes in fuel sets over time. This specific abatement mechanism is key to abatement in greenhouse gas emissions. Such emissions are directly related to the carbon content of fossil fuel, whereas filters and scrubbers are mostly used for local air pollutants, and have proven to be ineffective in decreasing greenhouse gas emissions. Insights from the spatial economics literature allow us to study changes in the geographic distribution of emissions and output over time. In our paper, firms are spatially related because of input-output linkages, inter-regional trade, and because firms compete across regions.

Methodologically we borrow from the large literature on production function estimation and dynamic discrete choice models. We build on the methodology of Murray Leclair (2024) to estimate a production function in which firms use different inputs (fuels). Following the work of Gandhi, Navarro, and Rivers (2020), Grieco, Li, and Zhang (2016), and Doraszelski and Jaumandreu (2013), we leverage firms' optimality conditions to pin down key substitution parameters. We do so without the need to impose timing restriction on firms production decisions. We then apply the conditional choice probability (CCP) approach of Hotz and Miller (1993) to estimate the fixed switching costs between input (fuel) sets. In order to characterize the aggregate elasticity of substitution between fuels, we also make a contribution to a related literature on the aggregation of firm behaviors (Oberfield and Raval, 2021).

Lastly, there is a set of closely related papers. First, Murray Leclair (2024) studies how environmental policies can relocate polluting production or induce an adoption of cleaner fuel sets in India. We complement this approach by introducing a similar framework into a standard model of trade with heterogeneous firms (Melitz, 2003). Taken together, our model is similar to recent work in the international trade literature in which firms make multiple discrete choices, such as the location of production/innovation (Caliendo and Parro, 2020; J. Liu, 2024; Fan, Lee, and Smeets, 2022).

Most importantly, Korea has implemented many environmental policies to achieve the industrial green transition. By contrast to India and many developing countries where fossil

fuels such as coal are still heavily used, Korea's energy consumption is now closer to developed countries and many firms have transitioned out of fossil fuels. Second, Kim (Forthcoming) studies how a spatial expansion of local environmental policies affect the spatial distribution of emissions and output. There are several differences, although they study the same country in similar periods. The pollutants of interest are different as we study greenhouse gases, not local air pollutants. This difference is important because such emissions are directly linked to the combustion of fossil fuels in production, and the resulting negative externality is global. Policy implications are different because of these spillovers across space and time. In addition, our policy of interest is more general as we study both national and regional environmental policies. Lastly, our model adds inter-temporal substitution in fuel sets to study transitions dynamics away from fossil fuels towards a new long-run steady state. Third, Xiang (2023) studies how environmental polices lead to leakage in the short run and clean innovation in the long run. However, they do not study abatement and fuel combustion, which is an important complementary mechanism that we consider.

2 Data

We study Korea because it has exhibited a striking electrification pattern and because it has introduced a number of environmental policies, some of which vary across space.

2.1 Source and Sample Selection

Our primary data come from Statistics Korea, specifically the Statistical Business Registers (SBR) and the Mining and Manufacturing Survey (MMS). The SBR is regularly updated; in this paper, we use the 2024 August version, spanning 2016–2022. These data include all establishments (roughly 110,000 each year for mining and manufacturing), providing information on five-digit industrial classification, sales, employment, location (accurate to eight decimal points in x–y coordinates), as well as energy use and greenhouse gas (GHG) emissions by fuel type (coal, oil, gas, electricity, and others). Energy use is measured in ton of oil equivalent (toe). GHG includes CO_2, N_2O, and CH_4 in ton of CO_2 equivalent (tCO2eq). GHG is calculated from fuel use by multiplying the fuel-specific carbon content, which has been changing over time. The MMS also covers the years 2016–2022 but focuses on establishments with more than ten employees (around 80,000 establishments each year). Most importantly, it provides detailed employment information (regular, temporary, etc.), various cost-side data (wages, fuel and electricity spending, intermediate materials, information on R&D, etc.), and capital information (machinery, land, etc.). We merge these two datasets

for our analysis.

In order to avoid survey errors, we restrict attention to mining and manufacturing establishments that report positive electricity use, have non-missing value-added, and have a valid five-digit industry classification. We focus on Scope 1 GHG emissions originating from coal, oil, and gas. For further details on how we compute emissions factors and related metrics, see appendix. We conduct concordance to reflect a change in the classification in 2017 from the 9^{th} KSIC to the 10^{th} KSIC (see Appendix for more details). Then, we categorize industries into two broad groups—heavy and light—based on the Korean Standard Industry Classification (KSIC). Heavy industry includes two-digit KSIC codes that are typically associated with higher fossil fuel and energy usage (e.g., coal mining, petroleum product manufacturing, chemical production, and basic metals). They therefore tend to have higher greenhouse gas emissions and are more likely to be targeted by environmental policies. Light industry comprises the remaining KSIC codes within mining and manufacturing.

We then define regional units corresponding to a district-equivalent area, forming 250 districts in total. This is the smallest regional scale at which environmental policies are designed and implemented. Where district-level information is incomplete, we fill in missing values with the best available information. Ultimately, only one observation remains with no location details at all. Additionally, districts are harmonized to match the 2022 definitions (see Appendix for more details).

3 Environmental Policy

Table 1 summarizes six environmental policies that targeted fossil fuel use and air pollutant emissions. There are two that explicitly targeted fuel use, other two that targeted greenhouse gas emissions, and the other two that targeted local air pollutant emissions. Four out of six policies have regional variations. See Figure 1 for the difference. Four out of six policies have firm- or plant-level variations. The first two policies regulate the use of certain fuel types in specific regions. The third and fourth regulate greenhouse gas emissions of large polluting firms without regional variations. The fifth and sixth regulate local air pollutant emissions (NO_x, SO_x, or TSP) of large polluting plants with regional variations.

4 Motivating facts

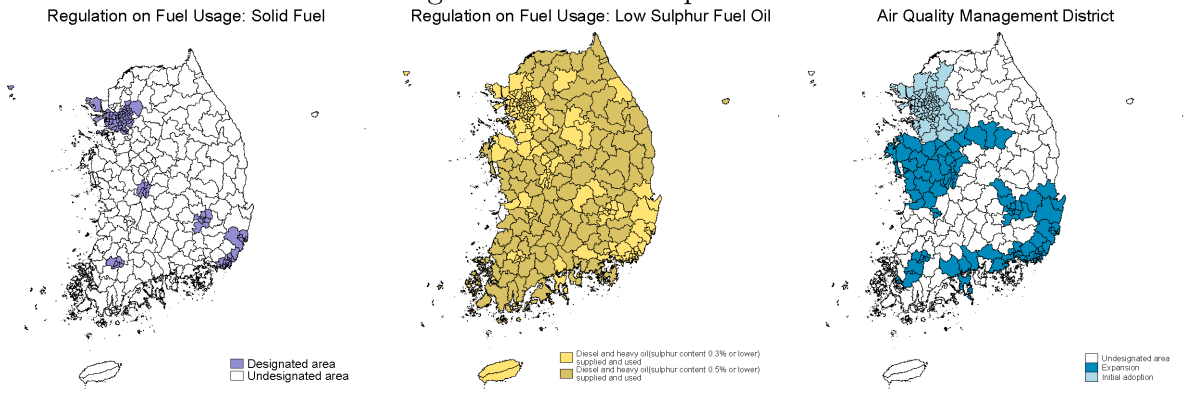
Between 2011 and 2022, the Korean government introduced environmental policies that influenced industrial decarbonization. We document a number of interesting facts associated with these policies. Plant-level electrification rose substantially, from roughly 35% to 65%.

Table 1: Current environmental policies

Regulation	System	Emissions source	Spatial Variation	Unit	Start
Fuel type 1	C&C	Coal, Coke, Wood	Local	District	2008
Fuel type 2	C&C	Fossil fuel	Local	District	2008
Greenhouse gas (Quotas)	Quotas, C&C	Fossil fuel, Tech	Global	Firm	2008
Greenhouse gas (CAT)	Cap-and-trade	Fossil fuel, Tech	Global	Firm	2015
Local air pollutant	C&C	Fossil fuel, Tech	Global	Plant	2017
Local air pollutant (CAT)	Cap-and-trade	Fossil fuel, Tech	Local	Plant	2008, 2020

Notes: C&C refers to command and control, which often ban specific production technologies or specific fuels. Quotas impose limits on emissions. Cap-and-trade (CAT) controls emissions allowances and allow trade.

Figure 1: Individual policies



Notes: Only local environmental regulations are plotted to capture regional policy variations.

Decomposition of greenhouse gas emissions indicates that a technique effect (plant-level adjustments) lowered emissions, countering increases from output growth and output reallocation across plants. We also find significant regional variations, with more urban districts facing stricter regulations while experiencing higher larger plant-level substitution towards cleaner energy, but, somewhat counterintuitively, higher output growth. Also, the least regulated districts experienced high plant-level substitution towards cleaner energy.. Lastly, we find significant plant/firm heterogeneity, especially in terms of emissions intensities. Unlike level variables such as GHG emissions, energy use, and value-added, emissions intensities have fatter tails and skewed distributions. This is in line with Lyubich, J. Shapiro, and Walker (2018) that documents firm heterogeneity in pollution in the U.S. and points out the importance of considering this heterogeneity in the design of environmental policy. Details can be found inappendix.

4.1 Aggregate trends

4.1.1 Fuel set Transition

One of the key objects of the green transition is the extensive margin of fuel use, or fuel sets (types of fuels used in production). Compared to the intensive margin, the extensive margin is more rare as it is associated with large fixed costs (Murray Leclair (2024)). For example, plants have to buy new machinery in order to stop using coal furnaces and to start using electric ones. In this section, we show the aggregate trend and regional variations in industrial decarbonization.

Fuel set Distribution We first summarize the distribution of fuel sets. Table 2 provides the summary statistics of the eight fuel sets used in the mining and manufacturing industry - in terms of value added, energy use, greenhouse gas emissions, and the number of plants. We denote the eight fuel sets using the first letter of each fuel type in a fuel set in an alphabetical order: EG={Electricity, Gas}, EGO={Electricity, Gas, Oil}, EO={Electricity, Oil}, E={Electricity}, CEO={Coal, Electricity, Oil}, CE={Coal, Electricity}, CEGO={Coal, Electricity, Gas, Oil}, and CEG={Coal, Electricity, Gas}. We decide not to study renewable because (1) they are rarely used as direct energy sources, and (2) they are hard to price because of the in-house generation.[1]

There are several patterns emerging from Table 2. First, in terms of value added and the number of plants, plants in EG, EGO, EO, and E account for a large share of each. However,

[1]Without loss of generality, we can aggregate electricity and renewable because renewable is highly likely to be used as a source of electricity. But this does not create a significant change since plants that use renewable are rare.

Table 2: Distribution of Selected Variables by Fuel Set

All industries in 2016					All industries in 2022				
Fuel Set	Value added	Energy	GHG	# plants	Fuel Set	Value added	Energy	GHG	# plants
EG	0262	0.056	0.02	0.09	EG	0.14	0.04	0.02	0.06
EGO	0.29	0.22	0.15	0.08	EGO	0.43	0.32	0.16	0.04
EO	0.25	0.42	0.33	0.48	EO	0.17	0.31	0.17	0.32
E	0.17	0.02	0.00	0.36	E	0.24	0.02	0.00	0.58
CEO	0.00	0.04	0.04	0.00	CEO	0.00	0.04	0.05	0.00
CE	0.00	0.00	0.00	0.00	CE	0.00	0.00	0.00	0.00
CEGO	0.02	0.17	0.31	0.00	CEGO	0.01	0.10	0.20	0.00
CEG	0.01	0.08	0.15	0.00	CEG	0.02	0.28	0.41	0.00
Total	1	1	1	1	Total	1	1	1	1

Notes: All active plants in each year are included in the summary statistics. N/A means that there are no observations in the corresponding cell. The sample is limited to plants with positive electricity use and non-missing value-added and 5-digit industry classification. The numbers are rounded to two decimal places. To calculate shares, we divide the value added, energy use, greenhouse gas emissions, and the number of plants in each fuel set by the totals.
Sources: SBR and MMS

in terms of energy use, EG, EGO, EO, and CEGO take the top four. In terms of greenhouse gas emissions, EGO, EO, CEO, and CEGO take the majority. Second, such discrepancies imply that plants in some fuel sets use significantly large amount of energy or emits more than the others. Third, one notable fuel set is E where only electricity is used in production. As will be shown later, this is where the economy has been headed for years.

Fuel set Transition Table 3 presents the transition between fuel sets from 2020 to 2022 in all sectors, heavy industry, and light industry, respectively. Several notable patterns emerge. First, fuel sets are persistent over time, as the majority of diagonal elements in the table exceeds 0.5. Second, once we omit CEO, CE, CEGO, and CEG—those that are rarely used—the fuel set E, in which only electricity is used, functions as an absorbing state because every other set tends to shift to E, and transitions out of E are relatively rare.

Figure 2 illustrates the shares of fuel sets over 30 years. The actual shares of fuel sets from 2016 to 2022 are shown with filled dots, and the imputed shares from 2023 are shown with empty dots. We use the same color for each fuel set and employ three-year moving averages to smooth transitions. For example, for 2016 we use 2016 data; for 2017, we use 2016 and 2017 data; and for 2018, we use 2016, 2017, and 2018 data. This pattern remains robust when using t-1, t, and t+1 periods instead.

The imputation proceeds as follows. We take 2022 as the baseline period, then calculate transition matrices using three-year moving averages. For the first transition matrix, we use 2020, 2021, and 2022 transitions. For another iteration, we take 2023 as the baseline and

use the transition matrix that pools 2021, 2022, and 2023 data. Additionally, for transition matrices, we use predicted values from regressions on 5-digit industry and year fixed effects, including interacted ones, to maintain consistency with the actual data points. As a result, the figure depicts the transition and steady state of the economy given the initial 2022 fuel set distribution.[2]

Overall, the results suggest a transition away from fossil fuels. This contrasts with developing countries such as India, where coal and other fossil fuels are still used extensively. Specifically, there are two strong and rapid trends in the economy. One is the electrification of industrial plants, observed in the left panels. According to this projection, despite some sectoral differences, transitions to electricity will overshadow other changes, and in roughly 10 years, electricity will become the most prevalent fuel set in the economy. Even between 2016 and 2022, we see a massive increase in electrification, from roughly 35% to 60% of all plants. This is one of the main motivating factor for this paper. Additionally, the pattern is not driven by plant entry and exit, and much of the variation in electrification is due to existing plants switching out of fossil fuels. When abstracting from entry/exit, we find that electrification went from 30% to 50% of all plants.[3]

This development has two notable implications. First, it indicates that environmental policies promoting a green transition have worked, as industrial plants move away from dirtier fuel usage—unlike India, where coal use has risen (Murray Leclair, 2024). Second, it raises the possibility of leakage into the power generation sectors (scope 2 emissions). Electricity may appear clean from an industrial plant's perspective, but how that electricity is produced is crucial for total emissions (Kim, Forthcoming).

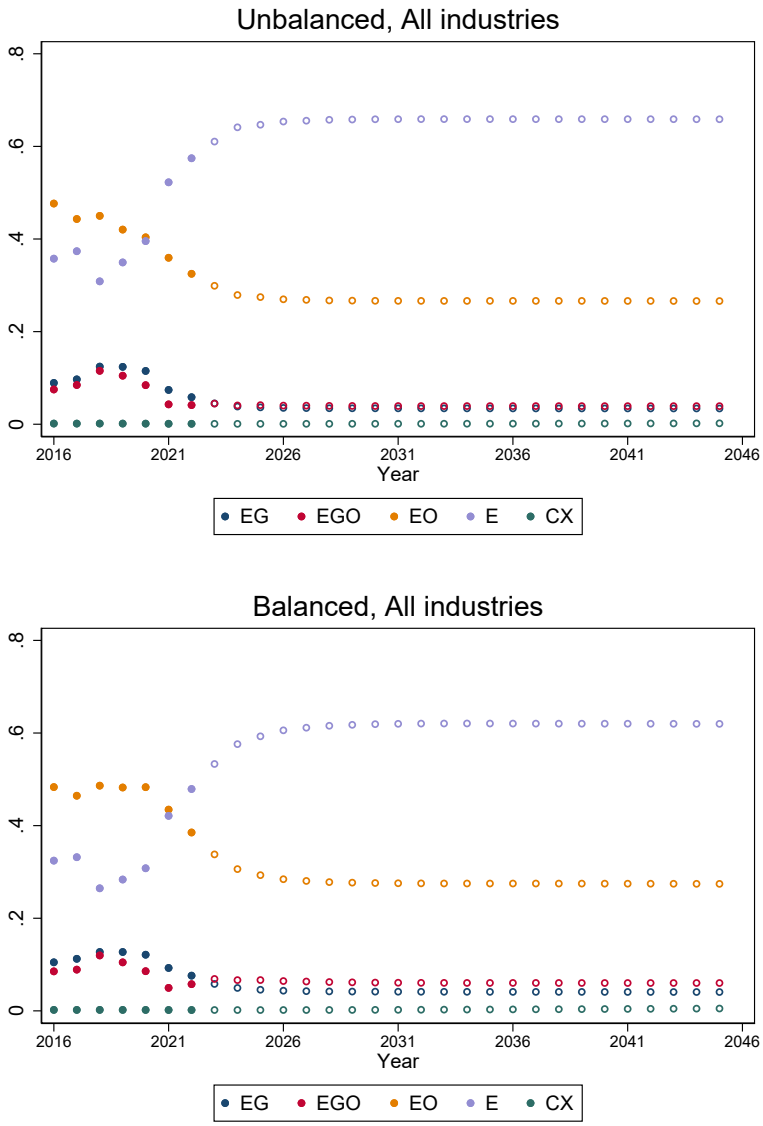
4.1.2 Emissions Decomposition

We construct Scope 1 GHG emissions in carbon dioxide equivalent following the commonly used Global Warming Potential (GWP) method. GHG emissions include CO_2 emissions, CH_4 emissions, and N_2O emissions from coal, oil, and natural gas. For now, we abstract from local air pollutants. Scope 1 emissions originate from industrial production. Aggregate GHG emissions are the sum of these emissions across regions (n) and industries (j). Denoting

[2]More formally, The projection is calculated as follows: Let A be the initial (2022) distribution in a vector, and let M_1 be the first transition matrix. Each matrix is normalized so that there are only eight fuel sets in total, and each element is expressed as a share. We then calculate yearly shares: A corresponds to the distribution in 2022, AM_1 corresponds to the distribution in 2023, AM_1M_2 corresponds to the distribution in 2024, and so on. These are plotted over many periods until convergence. We perform the same exercise in all sectors, heavy industry, and light industry.

[3]The balanced panel data is the case where we drop plants with missing, entry, and exit between 2016 and 2022. The unbalanced panel data is the case where we do not drop any.

Figure 2: Fuel set transition



Notes: The filled dots (2016-2022) are from data while the empty dots (2023-) are projection. The sample is limited to plants with positive electricity use and non-missing value-added and 5-digit industry classification.
Sources: SBR and MMS

Table 3: Fuel set Transition

$t-1 \backslash t$	EG	EGO	EO	E	CEO	CE	CEGO	CEG	Total
EG	**0.49**	0.07	0.13	0.32	0.00	0.00	0.00	0.00	1
EGO	0.03	**0.49**	0.20	0.28	0.00	0.00	0.00	0.00	1
EO	0.02	0.03	**0.65**	0.30	0.00	0.00	0.00	0.00	1
E	0.02	0.01	0.13	**0.85**	0.00	0.00	0.00	0.00	1
CEO	0.00	0.0	0.15	0.00	**0.69**	0.00	0.15	0.00	1
CE	0.00	0.0	0.00	0.00	**1.00**	**0.00**	0.00	0.00	1
CEGO	0.00	0.20	0.00	0.10	0.00	0.00	**0.70**	0.00	1
CEG	0.00	0.00	0.00	0.00	0.00	0.000	0.50	**0.50**	1

Notes: The sample is limited to plants with positive electricity use and non-missing value-added and 5-digit industry classification. We include all active plants in the table. We choose ratios over counts by dividing the number of each transition with the initial number of plants with that intial fuel set. The shares are rounded to two decimal places.
Sources: SBR and MMS

greenhouse gas emissions in ton of CO_2 equivalent ($tCO2eq$) by GHG

$$GHG = \sum_{n,j} GHG^{n,j}$$

and each component can be computed by multiplying emissions factor κ^f with fossil fuel f use $e^{n,j,f}$ in ton of oil equivalent (toe), where f denotes coal, oil, and gas. Emissions factors are allowed to change over time as they were in the past policy implementation. Quantities of fossil fuels are summed across all plants that operate in a given industry and region pair: $e^{n,j,f} = \int_{\omega \in \Omega} e^{n,j,f}(\omega)\, d\omega$.

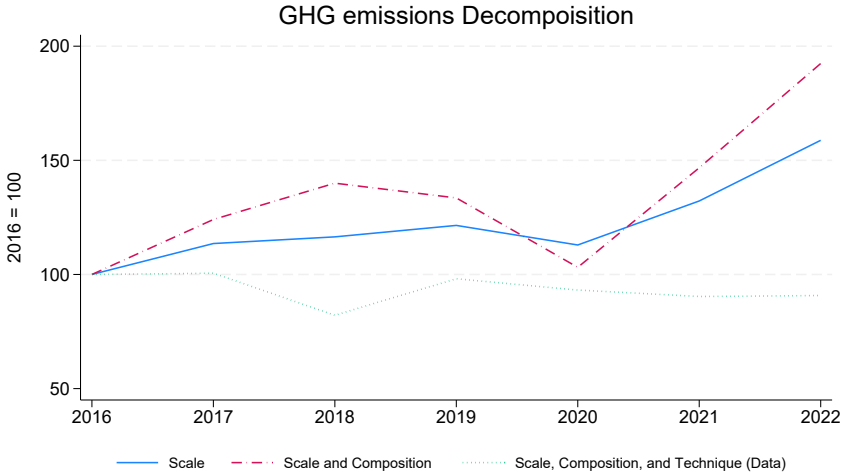
$$GHG^{n,j} = \sum_{f} \kappa^f e^{n,j,f}$$

In Section 4.1.1, we studied an aggregate trend in the extensive margin where fuel sets changed over time. Here we complement such a trend with that of the intensive margin. We decompose GHG emissions from 2016 to 2022 setting 2016 as the base period. Let X denote value added, and j denote 5-digit KSIC sectors. Then, we can decompose the total emissions as follows

$$\begin{aligned} GHG &= \sum_j GHG^j \\ &= \underbrace{X}_{\text{Scale}} \sum_j \underbrace{\frac{X^j}{X}}_{\text{Composition}} \underbrace{\frac{GHG^j}{X^j}}_{\text{Technique}} \end{aligned} \tag{1}$$

The scale effect captures the variation in emissions that is only due to changes in aggregate

Figure 3: Aggregate Decomposition



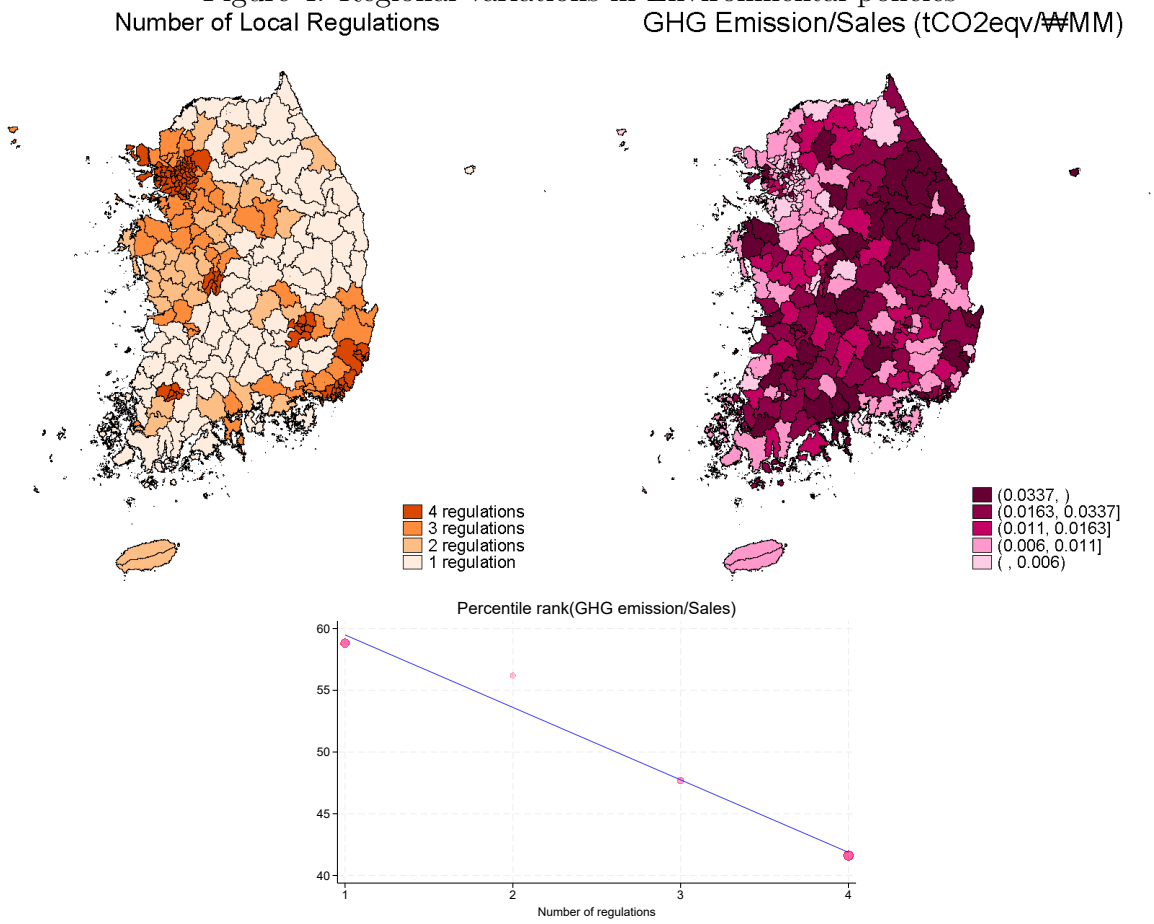
Note. This figure plots observed and counterfactual trends in GHG emissions based on the statistical decomposition from Equation 1. The sample is limited to plants with positive electricity use and non-missing value added.
Sources: SBR and MMS

value added, keeping everything else constant to the base period. The composition effect captures variation in emissions that is only due to reallocation of value added across sectors. Finally, the technique effect captures variation in emissions that is only due to firm-level adjustments in emissions intensity (e.g., by substituting towards cleaner fuels). The scale, composition, and technique effect displays the actual observed emissions trends, which include the scale, composition, and techniques effects since the base period. The result is summarized in Figure 3. We find significant improvement in emissions intensity over the period while the scale effect and the composition effect maintained or worsened emissions.

4.2 Regional variations

So far, we have seen two aggregate trends that reflect a green transition in the Korean industry. We see a trend towards electrification of mining and manufacturing processes, whereby firms drop fossil fuels, and a large technique effect, suggestive of significant substitution towards cleaner fuels at the intensive margin. In this section, we also find some interesting regional variations. First, districts in more urban areas (most notably in areas near Seoul and Busan) tend to face more environmental regulations and, in general, firms in those districts have lower emissions intensities. Figure 4 shows the number local environmental policies by district (panel 1), greenhouse gas intensities across districts (panel 2), and a negative correlation between the two (panel 3). The third panel suggests that environmental policies may

Figure 4: Regional variations in Environmental policies

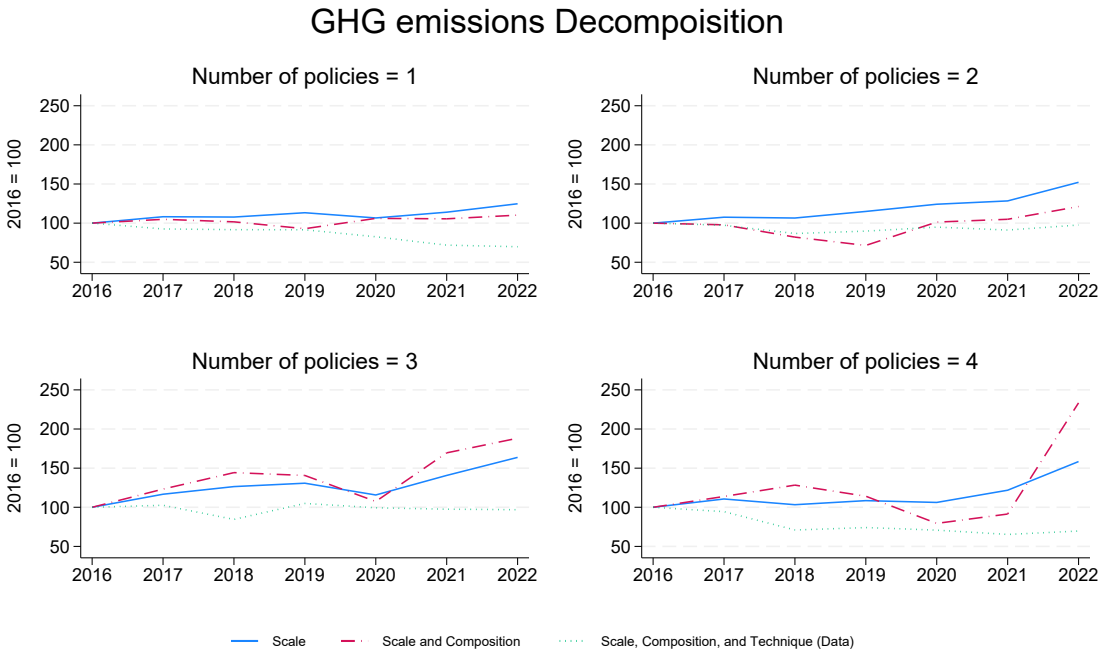


Notes: In the third panel, we use the rank of regional GHG intensity for better visualization. The size of each dot represents the number of districts corresponding to a specific number of local environmental policies.

have been effective at reducing emissions, with the caveat that most of these policies were implemented before the start of our sample. It should only be interpreted as a correlation only.

However, variation in environmental regulation intensity does not necessarily reflect canonical patterns in the evolution of emissions and output over time. For instance, we show in Figure 5 that more regulated districts had larger technique effect between 2016 and 2022. Details of the regional decomposition can be found in the appendix. Moreover, the most regulated districts were also the ones that grew the most. While other factors could be explaining output growth, we believe that heterogeneous treatment effects could explain these patterns. In other words, the salience of any environmental regulation may vary across regions. A regulation could have differential impacts on different regions based on the ability of firms to absorb the regulation and adopt cleaner energy sources. Firms in rural areas that face only one regulation could be more exposed due to more emissions intensive fuel sets at

Figure 5: Regional Decomposition



Notes: These figures plot observed and counterfactual trends in GHG emissions based on the statistical decomposition from Equation 1. The sample is limited to plants with positive electricity use and non-missing value-added and 5-digit industry classification. The panels capture the decomposition results of regions differentiated by the number of local environmental policies in 2022. The regions in the top left panel have only one local environmental policies.
Sources: SBR and MMS

the baseline and lower average productivity, making the green transition more difficult. A rich model of production and fuel substitution can help us understand how firms differentially respond to regulation, and how these responses impact regional output, regional wages, and inter-regional trade patterns. This is what we discuss in the next section.

5 Causal inference (in progress)

- Use satellite data, but there are some caveats/food for thoughts
  - Persistence (also known as carbon cycle) might be mitigated if we also observe heavy ones or the policy of interest was strong or put past emissions as covariates
  - Globalness (spatial spillover) might be mitigated with granular units
  - Filter and scrubbers are more about local air pollutant emissions so this maps to emissions from fossil fuel use tightly
- Method: model-driven framework

- Regression discontinuity in space or Difference in differences: promising
- Shift-share: unlikely

6 Model

In this section, we develop a dynamic spatial general equilibrium model of trade and emissions to see how national or local environmental policies affect the geographic distribution of greenhouse gas emissions and economic output in the country. We embed a dynamic discrete choice of fuel sets into a spatial general equilibrium model of trade, extending it to have greenhouse gas emissions. We consider an economic environment with internal geography. The economic environment consists of N regions indexed by i and n, and J sectors which labeled by j and k. Location n features an initial mass of households ($L^{n,j}$), an initial mass of firms with fuel set $\mathcal{F}$, ($M_0^{n,j}(\mathcal{F})$), an initial endowment of capital structures ($K^{n,j}$), goods mobility frictions ($\tau^{ni,j}$) between n and i, and fuel-switching costs ($f^{\mathcal{F}\mathcal{F}'}$) from $\mathcal{F}$ to $\mathcal{F}'$ in sector j. Here fuel sets are the sets of fuel types used in production, which we discussed extensively in previous sections. We assume no changes in $L^{n,j}$ and $K^{n,j}$ and normalize them s.t.$\sum_{n,j} L^{n,j} = 1$ and$\sum_{n,j} K^{n,j} = 1$. For now, we assume that the total number of firms in the economy is exogenous and constant at $M_0^{n,j}$in each region.

We treat South Korea as a small open economy, so spot market prices for fuels are set internationally and are unaffected by Korean regulations. We motivate this assumption based on the facts that Korea imports around 95% of its energy source, and even up to 100% for natural gas and oil. However, we allow for regulations to introduce shadow prices on different fuels, so the actual fuel price that firms pay may vary across regions. We assume that fuels can be traded across sectors and regions frictionlessly so we abstract from fuel transportation costs. Time is discrete, and we denote it by $t = 0, 1, 2, ...$ We only use subscripts to denote time. Agents make decisions every period. The fuel set choice of firms is dynamic while the rest is static. We drop time subscripts when unnecessary.

There are four types of agents. Households decide how much to consume, supply labor, and rent capital structures, and firms decide which fuel set to use dynamically, how much to produce and sell across locations statically. The government collects pollution tax. We start by describing the problem of the household and then set up the problem of the firm. After deriving the market clearing conditions, we define the equilibrium of the model.

6.1 Households

A representative household in each location n and sector j supplies a unit of labor inelastically at a competitive market wage, $w^{n,j}$, rents capital structure inelastically at a competitive rental rate, $r^{n,j}$, and consumes their real income $\left(w^{n,j}L^{n,j} + r^{n,j}K^{n,j}\right)/P^n$ where P^n is the price index in location n. At each period, households decide how to allocate consumption over local final goods from all sectors. The consumption basket is defined as

$$C^n = \prod_{k=1}^{J} \left(C^{n,k}\right)^{\alpha^{n,k}}$$

where $\sum_{k=1}^{J} \alpha^{n,k} = 1$ for all n. $C^{n,k}$ denotes the consumption of final goods from sector k of a household located in n. The ideal local price index is given by $P^n = \prod_{k=1}^{J} \left(P^{n,k}/\alpha^{n,k}\right)^{\alpha^{n,k}}$.

Further, emissions negatively affect utility, but household cannot impact them with their decisions, making emissions a pure negative externality. We borrow a damage function from Nordhaus (2015) and Shapiro (2016) to capture the reduced-form effect of emissions on utility. Assuming logarithmic preferences, we have the following static utility

$$u^{n,j} = \log\left(C^{n,j}\right) + \log\frac{1}{1 + \left(\Upsilon \times CO_{2e}\right)^2}$$

where Υ is a parameter that maps GHG emissions (CO_{2e}) to social damages, and will determine the social cost of carbon. Since we deal with GHG emissions, regions and sectors do not matter such that $CO_{2e} = \sum_{n,j} CO_{2e}^{n,j}$. The quadratic term is a common practice in the literature that captures non-linear damages. The household aggregates its static utility over time with a discount factor β

$$U_t^{n,j} = \sum_{t=0}^{\infty} \beta^t u_t^{n,j}$$

6.2 Production

The production structure builds on the multi-sector model with sectoral linkages (Caliendo and Parro, 2015). We depart from these frameworks by introducing environmental policies, GHG emissions, and dynamic decisions of firms on which fuel sets to use. We first describe the production of final goods and then the production of intermediate goods.

6.2.1 Final Good Producer

At each location and sector, a final good producer produces a final sectoral composite good with a constant elasticity of substitution (CES) production function. In each region n and sector j, there is a mass of firms $\Omega^{n,j}$ producing distinct varieties. Within each sector and region, firms vary based on their choice of fuel set $\mathcal{F} \subseteq \mathbb{F}$and their productivity z. As will be shown later, this difference comes from idiosyncratic shocks in fuel set decisions. Then, indexing a firm with ω, we have a final sectoral composite good that aggregates varieties

$$\begin{aligned} Q^{n,j} &= \left(\sum_{i=1}^{N} \int_{\Omega^{i,j}} \left(q^{in,j}\left(\omega\right) \right)^{(\sigma^j - 1)/\sigma^j} d\omega \right)^{\sigma^j/(\sigma^j-1)} \\ &= \left(\sum_{i=1}^{N} \sum_{\mathcal{F} \subseteq \mathbb{F}} M^{i,j}\left(\mathcal{F}\right) \int \left(q^{in,j}\left(\mathcal{F}, z\right) \right)^{(\sigma^j - 1)/\sigma^j} dF^{n,j}\left(z \mid \mathcal{F}\right) \right)^{\sigma^j/(\sigma^j-1)} \end{aligned}$$

where $M^{in,j}\left(\mathcal{F}\right)$ denotes the number of varieties produced in location i and sector j by firms with fuel set $\mathcal{F}$, and σ^j denotes the elasticity of substitution across varieties. We explicitly allow the distribution of productivity conditional on each fuel set to vary by industry, region, and years. This will have important implications to study the ability of firms in different regions to transition out of fossil fuels based on their productivity. The demand in region n for sector j goods produced in region i is given by

$$q^{in,j}\left(\mathcal{F}, z\right) = \left(\frac{p^{in,j}\left(\mathcal{F}, z\right)}{P^{n,j}} \right)^{-\sigma^j} \frac{X^{n,j}}{P^{n,j}} \tag{2}$$

where $p_t^{in,j}$ is the price in region n of varieties in sector j produced in region i, and $X^{n,j}$ is total expenditure in location n and sector j. The ideal sectoral price index $P^{n,j}$ is then given by

$$P^{n,j} = \left(\sum_{i=1}^{N} \sum_{\mathcal{F} \subseteq \mathbb{F}} M^{i,j}\left(\mathcal{F}\right) \int \left(p^{in,j}\left(\mathcal{F}, z\right) \right)^{1-\sigma^j} dF^{n,j}\left(z \mid \mathcal{F}\right) \right)^{1/(1-\sigma^j)} \tag{3}$$

6.2.2 Intermediate Good Producers

Producers of intermediate varieties are monopolistically competitive firms, who make forward looking decisions on fuel sets. The dynamics decisions are subject to fuel-switching costs as well as idiosyncratic shocks. Given their fuel sets, firms decide how much to produce and sell in domestic and foreign markets to maximize profits.[4] The production decision of the

[4]Here we differentiate locations by foreign and domestic to keep the analogy for international trade.

firm is influenced by local and global demand, trade costs, the price of local factors (labor, capital structures, and materials), local pollution taxes, productivity, and global fuel prices. We describe first the static profit maximization problem of a firm given its location, sector, fuel set, and productivity. After that, we move to the dynamic fuel set choice problem.

Static Production Intermediate good producers maximize their profits. Producers of intermediate varieties in location n and sector j demand labor $l^{n,j}$, capital structures $k^{n,j}$, and energy aggregate $e^{n,j}$. The production technology is differentiated by common technology parameters that vary across industries and (potentially) regions, hicks-neutral productivity z,and a fuel set $\mathcal{F} \subseteq \mathbb{F}$. The outer production function (production technology to produce output) in location n and sector j for a firm with productivity z and fuel set $\mathcal{F}$ is given by

$$q^{n,j}\left(\mathcal{F}, z\right) = z\left(l^{n,j}\right)^{1-\xi^{n,j}-\zeta^{n,j}}\left(k^{n,j}\right)^{\xi^{n,j}}\left(e^{n,j}\left(\mathcal{F}\right)\right)^{\zeta^{n,j}} \tag{4}$$

where $\{\zeta^{n,j}, \xi^{n,j}, 1-\xi^{n,j}-\zeta^{n,j}\}$ are the share of energy, capital, and labor in value added, respectively. For a fuel set $\mathcal{F}$, the inner production function (production technology to aggregate fuel uses into energy aggregate) is given by a CES aggregate of all fuel quantities $e^{n,j,f}$ multiplied by average fuel-specific productivity $\beta^{j,f}$

$$e^{n,j}\left(\mathcal{F}\right) = \left(\sum_{f\in\mathcal{F}} \beta^{j,f}\left(\mathcal{F}\right)\left(e^{n,j,f}\right)^{\frac{\lambda^j-1}{\lambda^j}}\right)^{\frac{\lambda^j}{\lambda^j-1}}$$

where $\sum_{f\in\mathcal{F}} \beta^{j,f}\left(\mathcal{F}\right) = 1, \forall j, \mathcal{F} \subseteq \mathbb{F}$. From the CES structure, we have the ideal energy price index

$$\tilde{p}^{n,j}\left(\mathcal{F}\right) = \left(\sum_{f\in\mathcal{F}}\left(\beta^{j,f}\left(\mathcal{F}\right)\right)^{\lambda^j}\left(\tau^{n,f}+p^f\right)^{1-\lambda^j}\right)^{\frac{1}{1-\lambda^j}} \tag{5}$$

where p^f is the world price of fuel f and $\tau^{n,f} \geq 0$ denotes per-unit pollution taxes for fuel f in region n. $\tau^{n,f}$ will be interpreted as shadow prices below. Note that, as long as fuels are gross substitutes $\lambda^j > 1$, there is a tradeoff between the gains from variety from having more fuels in one's set, and the impact of variation in average fuel productivity across fuel sets. If average fuel productivity was constant across fuel sets, firms would always want to use more fuels to access additional substitution margins. Moreover, there would be a positive gradient between the number of fuels and productivity with any fixed switching costs. This may be at odds with the observed pattern of electrification in the data. For instance, firms that are transitioning away from fossil fuels are likely replacing existing processes with electricity, which would change the importance of electricity in the production process (captured by

$\beta^{j,f}(\mathcal{F})$).

We assume that labor and capital are immobile across sectors and regions while fuels are perfectly mobile across sectors and regions. We denote factor prices by $w^{n,j}$ for labor, $r^{n,j}$ for capital structures, and $\tilde{p}^{n,j}$ for energy. From the cost minimization problem of the firm, we obtain the unit cost of production denoted by $x^{n,j}$ as

$$x^{n,j}(\mathcal{F}) = B^{n,j}\left(w^{n,j}\right)^{1-\xi^{n,j}-\zeta^{n,j}}\left(r^{n,j}\right)^{\xi^{n,j}}\left(\tilde{p}^{n,j}(\mathcal{F})\right)^{\zeta^{n,j}} \tag{6}$$

where $B^{n,j}$ is a constant. Firms sell their products locally and to other markets subject to (non-policy) trade costs. The trade costs are transportation costs that take the standard iceberg formulation, where $d^{ni,j} \geq 1$ is the cost of shipping goods from n to i in industry j. Firms maximize profits by taking into account the demand for their goods; namely (Equation 2). Let us denote by $\pi^{ni,j}(\mathcal{F})$ to the gross profit of a firm in sector j located in n and selling goods to i with fuel set $\mathcal{F}$. The problem of the firm is given by

$$\pi^{ni,j}(\mathcal{F},z) = \underset{p^{ni,j}\geq 0}{max}\left\{p^{ni,j}q^{ni,j}(\mathcal{F},z) - \frac{x^{n,j}(\mathcal{F})}{z}d^{ni,j}q^{ni,j}(\mathcal{F},z);\ \text{subject to (Equation 2)}\right\}$$

The solution to this problem is the standard mill pricing

$$p^{ni,j}(\mathcal{F},z) = \frac{\sigma^j}{\sigma^j-1}\frac{d^{ni,j}x^{n,j}(\mathcal{F})}{z} \tag{7}$$

Firms from industry j that locate production in n and have fuel set $\mathcal{F}$ and productivity z have total gross profits from selling domestically as well as to other locations, which is given by

$$\pi^{n,j}(\mathcal{F},z) = \sum_{i=1}^{N}\pi^{ni,j}(\mathcal{F},z) \tag{8}$$

where $\pi^{ni,j}(\mathcal{F},z) = p^{ni,j}(\mathcal{F},z)\,q^{ni,j}(\mathcal{F},z)/\sigma^j$.

Our focus is on the fuel set choice of firms, and how an environmental policy affects the decision of firms and in turn how this impacts the economic and pollution distributions. In what follows, we departure from the literature by introducing environmental policies, GHG emissions, and forward looking dynamics in the fuel set choice used for production.

Dynamic Choice on Fuel set We present a dynamic discrete fuel set choice. We denote by $v_t^{n,j}$ the value of a firm producing in sector j located in n at time t. Firms at time t have gross profits given by $\pi_t^{n,j}$ from (Equation 8), and decide whether to change their fuel sets next period. We assume that firms face idiosyncratic shocks to their future revenues each

period of time. We define $V_{t+1}^{n,j} \equiv E_t^{\epsilon}\left[v_{t+1}^{n,j}\right]$ to be the expected values of a representative firm over all the possible realizations of the idiosyncratic shocks where we denote the idiosyncratic shocks by $\epsilon_t^{n,j}$, and we assume firms discount the future by β. We drop location and sector superscripts as there is no location or sector choice of firms for simplicity. The value of a firm is then given by

$$v_t\left(\mathcal{F}, z\right) = \pi_t\left(\mathcal{F}, z\right) + \max_{\mathcal{F}' \subseteq \mathbb{F}} \left\{ \beta \mathbb{E}_t^{\epsilon} \left[\mathbb{E}_t^{z} \left[v_{t+1}\left(\mathcal{F}', z'\right) \mid \mathcal{F}, z \right] - f^{\mathcal{F}\mathcal{F}'} + \vartheta \epsilon_t^{\mathcal{F}'} \right] \right\} \tag{9}$$

where $f^{\mathcal{F}\mathcal{F}} = 0$. Although there is no differentiation between sunk and fixed costs, the costs related to clean innovation are close to sunk costs by nature (e.g., gas facilities replacing coal ones). The idiosyncratic shocks $\epsilon_t^{\mathcal{F}'}$ are i.i.d. realizations from a Type-I Extreme value distribution with zero mean and dispersion parameter ϑ. The parameter ϑ is important because it puts everything in dollars and also determines the persistence of fuel switching. Note that we are assuming that the fuel-switching cost is paid the next period, the period in which the firm starts producing with its new fuel set. Using the properties of the Type-I extreme value distributions, we obtain that the value of firms

$$V_t\left(\mathcal{F}, z\right) = \pi_t\left(\mathcal{F}, z\right) + \vartheta \ln\Big(\sum_{\mathcal{F}' \subseteq \mathbb{F}} \exp\left(\beta \mathbb{E}_t^{z} \left[V_{t+1}\left(\mathcal{F}', z'\right) \mid \mathcal{F}, z \right] - f^{\mathcal{F}\mathcal{F}'}\right)^{\frac{1}{\vartheta}} \Big) \tag{10}$$

Equation 10 indicates that the value of a firm depends on its current-period gross profits with the current fuel set and on the option value to change its fuel set in the future. We also get fuel set choice probabilities, as a function of initial fuel set and state variables (productivity and fuel set). We denote by $\varphi_t\left(\mathcal{F}' \mid \mathcal{F}, z\right)$ the fraction of firms with productivity z that decide to continue using a different fuel set $\mathcal{F}'$ tomorrow. Using properties of the Type-I extreme value distribution, we obtain

$$\varphi_t\left(\mathcal{F}' \mid \mathcal{F}, z\right) = \frac{\exp\left(\beta \mathbb{E}_t^{z}\left[V_{t+1}\left(\mathcal{F}', z'\right) \mid \mathcal{F}, z\right] - f^{\mathcal{F}\mathcal{F}'}\right)^{\frac{1}{\vartheta}}}{\sum_{\mathcal{F}'' \subseteq \mathbb{F}} \exp\left(\beta \mathbb{E}_t^{z}\left[V_{t+1}\left(\mathcal{F}'', z'\right) \mid \mathcal{F}, z\right] - f^{\mathcal{F}\mathcal{F}''}\right)^{\frac{1}{\vartheta}}} \tag{11}$$

for all $\mathcal{F} \in \mathbb{F}$. It follows that the fraction of firms that drop $\mathcal{F}$ is given by $\sum_{\mathcal{F}' \neq \mathcal{F}} \varphi_t\left(\mathcal{F}' \mid \mathcal{F}, z\right) = 1 - \varphi_t\left(\mathcal{F} \mid \mathcal{F}, z\right)$. Equation 11 is intuitive: the larger the value of producing with fuel set $\mathcal{F}'$ relative to using the other fuel sets, the larger the share of firms that decide to produce with fuel set $\mathcal{F}'$. In a general equilibrium, how economic circumstances affect the fuel set decision of firms will also depend on how the value to produce with each fuel set is also impacted by the shock, or a change in an environmental policy. From now on, we mainly focus on characterizing and quantifying the effect that an environmental policy has in this fuel set

decision.

Finally, we can determine the evolution of the mass of firms with fuel set $\mathcal{F}$ in each location n and sector j. Denote by $M_t(\mathcal{F}, z)$ the mass of firms with $(\mathcal{F}, z)$. Using the law of total probability with the fuel set choice probabilities, we obtain the following law of motion:

$$M_{t+1}(\mathcal{F}, z) = M_t(\mathcal{F}, z)\,\varphi_t(\mathcal{F} \mid \mathcal{F}, z) + \sum_{\mathcal{F}' \neq \mathcal{F}} M_t(\mathcal{F}', z)\,\varphi_t(\mathcal{F}' \mid \mathcal{F}, z) \tag{12}$$

where $M_t(\mathcal{F}, z) = M_0 \times Pr_t(\mathcal{F}, z)$ for a fixed number of firms. For now, we take M_0 as given abstracting away from firm entry and exit. $Pr_t(\cdot)$ is defined as the unconditional probability (share of firms) of using fuel set $\mathcal{F}$ with productivity z at t. The equilibrium condition (Equation 12) characterizes the evolution of the distribution of fuel sets used by firms in location n and sector j in our economy.

6.2.3 Micro-foundation for Pollution Taxes

In this section, we provide a micro-foundation for pollution regulation via a reduced form fuel f-specific per-unit pollution tax τ^f to the model. First, we show that standard policy instruments such as carbon taxes and fuel use quotas can be represented by fuel-specific shadow prices. We start with a carbon tax. Define emissions of carbon dioxide equivalent by GHG. Imagine firms are facing a per-unit carbon tax τ imposed on total emissions. This will show up as an additional cost in production, $-\tau GHG$. This production cost is the same as the additional production cost induced by per-unit taxes τ^f on different fuels, $-\sum_{f\in\mathcal{F}} \tau^f e^f$. To see this, we can redefine carbon emissions as the product of fuel quantities with emissions factors κ^f that map units of fuels to units of carbon dioxide equivalent

$$GHG = \sum_{f\in\mathcal{F}} \kappa^f e^f$$

The additional cost of production with a carbon tax can be rewritten as $\tau \sum_{f\in\mathcal{F}} \kappa^f e^f$. Then, any per-unit tax on fuels such that $\tau^f = \tau\kappa^f$ is equivalent to a carbon tax. While the level of the tax can vary across fuel with τ, the relative tax rate between two fuels is equal to the the relative emission content of both fuels: $\tau^f/\tau^{f'} = \kappa^f/\kappa^{f'}$.

We also show that binding fuel use quotas have a similar per-unit tax representation. Under such a quota, the cost-minimization can be rewritten as

$$\min_{e^f{}_{f\in\mathcal{F}}}\left\{\sum_{f\in\mathcal{F}}p^f e^f\right\} \quad s.t. \quad q\left(\mathcal{F}\right)=z\left[\left(l\right)^{1-\xi-\zeta}\left(k\right)^{\xi}\left(\left(\sum_{f\in\mathcal{F}}\beta_f\left(e_f\right)^{\frac{\lambda-1}{\lambda}}\right)^{\frac{\lambda}{\lambda-1}}\right)^{\zeta}\right]$$
$$e^f\leq\overline{e}^f$$

The Lagrangian can be written as

$$\mathcal{L}=\sum_{f\in\mathcal{F}}p^f e^f+\eta\left[\bar{q}\left(\mathcal{F}\right)-z\left[\left(l\right)^{1-\xi-\zeta}\left(k\right)^{\xi}\left(\left(\sum_{f\in\mathcal{F}}\beta_f\left(e_f\right)^{\frac{\lambda-1}{\lambda}}\right)^{\frac{\lambda}{\lambda-1}}\right)^{\zeta}\right]\right]+\sum_{f\in\mathcal{F}}\eta^f\left(e^f-\overline{e}^f\right)$$

Note that η captures the unit production cost of fuels while η^f captures the cost of quotas of fuel f. Assuming that the constraint is binding, the value of this shadow price will be such that the fuel f purchased of would be $\overline{e}^f$ if the firm was facing $p^f+\gamma^f$ as the true price. Hence, the binding quota is the same as an increase in per-unit prices.

6.3 Inter-fuel Elasticity of Substitution

In the following section, we study various elasticities of substitution from a permanent increase in the relative price of two fuels (f and f'). We abstract from industry and region subscript for better notation clarity, but aggregation is done within industry and region. This is a key model object that will allow us to understand how different regions respond differentially to environmental regulation. By solving the model, we find firm-level optimal quantify of fuel f for a firm with productivity z and fuel set $\mathcal{F}$ as

$$e^f\left(\mathcal{F},z\right)=\left(\Gamma\frac{\sigma-1}{\sigma}\right)^{\sigma}\left(\frac{z}{\tilde{x}}\right)^{\sigma-1}\zeta^{\zeta(\sigma-1)+1}\left(\frac{\beta^f}{p^f}\right)^{\lambda}\tilde{p}\left(\mathcal{F}\right)^{(\lambda-1)-\zeta(\sigma-1)}$$

where $\tilde{x}^n$ is the firm's unit cost, excluding the CES price of energy $\tilde{p}\left(\mathcal{F}\right)=\left(\sum_{f\in\mathcal{F}}\left(\beta^f\right)^{\lambda}\left(p^f\right)^{1-\lambda}\right)^{\frac{1}{1-\lambda}}$. The individual elasticity of substitution is very straightforward and only accounts for individual firm substitution at the intensive margin

$$\frac{\partial\ln\left(e^f\left(\mathcal{F},z\right)/e^{f'}\left(\mathcal{F},z\right)\right)}{\partial\ln\left(p^{f'}/p^f\right)}=\frac{\partial\left(\lambda\ln\left(\beta^f/\beta^{f'}\right)+\lambda\ln\left(p^{f'}/p^f\right)\right)}{\partial\ln\left(p^{f'}/p^f\right)}$$
$$=\lambda$$

6.3.1 Regional Static Elasticity of Substitution

The aggregate static elasticity of substitution (keeping fuel sets constant) is less straightforward to characterize but yields an intuitive results similar to Oberfield and Raval (2021). We first characterize the regional aggregate fuel quantity $e^{n,f}$

$$e^f = \sum_{\mathcal{F}:f\in\mathcal{F}} M(\mathcal{F}) \int e^f(\mathcal{F}, z)\, dF(z \mid \mathcal{F})$$

Similarly, for relative fuel quantities:

$$\frac{e^f}{e^{f'}} = \left(\frac{\beta^f}{\beta^{f'}}\right)^{\lambda} \left(\frac{p^{f'}}{p^f}\right)^{\lambda} \frac{\sum_{\mathcal{F}:f\in\mathcal{F}} \left(\tilde{p}(\mathcal{F})\right)^{(\lambda-1)-\zeta(\sigma-1)} M(\mathcal{F}) \int z^{\sigma-1} dF(z \mid \mathcal{F})}{\sum_{\mathcal{F}:f'\in\mathcal{F}} \left(\tilde{p}(\mathcal{F})\right)^{(\lambda-1)-\zeta(\sigma-1)} M(\mathcal{F}) \int z^{\sigma-1} dF(z \mid \mathcal{F})}$$

Right away, we can get some intuitive understanding of what will happen if relative fuel prices change. First, there will be some substitution at the intensive margin by individual firms at rate λ. Second, an increase in $p^{n,f'}/p^{n,f}$ raises the energy costs of firms using fuel sets that contain f' relative to fuel sets that contain f. Thus, we can expect that there will be an aggregate fuel substitution effect through output reallocation. However, note that this effect is due to the fact that there are different fuel sets. If there was only one large fuel set including every fuel, this output reallocation channel would disappear. Then, the elasticity of substitution is as follows

$$\lambda^n_{static} = \frac{\partial \ln\left(e^f/e^{f'}\right)}{\partial \ln\left(p^{f'}/p^f\right)} = \underbrace{\chi\lambda}_{\text{Individual substitution}} + \underbrace{(1-\chi)\left(1+\zeta(\sigma-1)\right)}_{\text{Output reallocation}}$$

where $\chi = 1 + \left(s^f - s^{f'}\right)\left(\beta^{f'}\right)^{\lambda}\left(p^{f'}\right)^{1-\lambda}$ and $s^{f'} = \frac{\sum_{\mathcal{F}:f\in\mathcal{F}}(\tilde{p}(\mathcal{F}))^{2(\lambda-1)-\zeta(\sigma-1)} M(\mathcal{F}) \int z^{\sigma-1} dF(z|\mathcal{F})}{\sum_{\mathcal{F}:f\in\mathcal{F}}(\tilde{p}(\mathcal{F}))^{(\lambda-1)-\zeta(\sigma-1)} M(\mathcal{F}) \int z^{\sigma-1} dF(z|\mathcal{F})}$. As expected, the regional elasticity of substitution is a mix of individual firm substitution (scaled by λ) and output reallocation (scaled by σ). Moreover, we can see that even when abstracting from firms adding or dropping new fuel types, the elasticity of substitution varies based on the distribution of fuel sets across regions.

6.3.2 Regional Dynamic Elasticity of Substitution

To introduce the role of fuel set switching, we study the elasticity of substitution from one period behind changes in relative fuel prices. As we will see, all of the effects will be captured by changes in the distribution of fuel productivity conditional on each fuel set. Indeed, consider an increase in $p^{f'}/p^f$. Since there are fixed costs underlying switching between fuel sets, the most productive firms are more likely to pay fixed costs to switch towards fuel sets that include fuel f or to drop fuel sets that include fuel f', whereas the

least productive firms are more likely to stick with fuel sets that include f. As a result, the distribution of productivity conditional on fuel sets that include f will shift upwards relative to fuel sets that include f', increasing the aggregate quantity of fuel f relative to fuel f'. We can start by rewriting the aggregation of fuel quantities, taking into account the distribution of productivity conditional of fuel sets $F\left(z \mid \mathcal{F}\right)$

$$e_t^f = \sum_{\mathcal{F}: f \in \mathcal{F}} \int_0^\infty M_0 e_t^f\left(\mathcal{F}, z\right) \sum_{\mathcal{F}' \subseteq \mathbb{F}} \left[Pr_{t-1}\left(\mathcal{F} \mid \mathcal{F}', z\right) Pr_{t-2}\left(\mathcal{F}' \mid z\right)\right] dF\left(z\right)$$

This needs to be unpacked. First, the number of firms (N) is constant in our model. Second, firms transition from one fuel set to another, which is why we need to use the law of total probability, to condition on the initial fuel set firms are starting from. The initial condition (or initial distribution of fuel sets, where firms start) is captured by $Pr_{t-2}\left(\mathcal{F}' \mid z\right)$ and can be treated as fixed (observed in data). Lastly, $Pr_{t-1}\left(\mathcal{F} \mid \mathcal{F}', z\right)$ is the probability that a firm with productivity z transitions from $\mathcal{F}'$ to $\mathcal{F}$. This is the main object of interest that will vary with relative fuel prices. We can use that information to characterize the dynamic regional elasticity of substitution

$$\begin{aligned}
\lambda_{dynamic} =& \frac{\partial \ln\left(e_t^f / e_t^{f'}\right)}{\partial \ln\left(p_{t-1}^{f'} / p_{t-1}^f\right)} \\
=& \lambda_{static}^n \\
&+ \frac{M_0}{\Omega_t^f} \sum_{\mathcal{F}: f \in \mathcal{F}} p_t\left(\mathcal{F}\right)^{(\lambda-1)-\zeta(\sigma-1)} \int \sum_{\mathcal{F}' \subseteq \mathbb{F}} \left[\frac{\partial Pr_{t-1}\left(\mathcal{F} \mid \mathcal{F}', z\right)}{\partial \ln\left(p_{t-1}^{f'} / p_{t-1}^f\right)} Pr_{t-1}\left(\mathcal{F} \mid \mathcal{F}', z\right) Pr_{t-2}\left(\mathcal{F}' \mid z\right)\right] dF\left(z\right) \\
&- \frac{M_0}{\Omega_t^{f'}} \sum_{\mathcal{F}: f' \in \mathcal{F}} p_t\left(\mathcal{F}\right)^{(\lambda-1)-\zeta(\sigma-1)} \int \sum_{\mathcal{F}' \subseteq \mathbb{F}} \left[\frac{\partial Pr_{t-1}\left(\mathcal{F} \mid \mathcal{F}', z\right)}{\partial \ln\left(p_{t-1}^{f'} / p_{t-1}^f\right)} Pr_{t-1}\left(\mathcal{F} \mid \mathcal{F}', z\right) Pr_{t-2}\left(\mathcal{F}' \mid z\right)\right] dF\left(z\right)
\end{aligned}$$

As discussed earlier, the elasticity is intuitive, aside from characterizing $\frac{\partial Pr_{t-1}(\mathcal{F}|\mathcal{F}',z)}{\partial \ln\left(p_{t-1}^{f'}/p_{t-1}^f\right)}$ which isn't trivial. Indeed, high productivity firms adopt fuel sets that include f (first effect) and drop fuel sets that include f' (second effect), increasing $e_t^f / e_t^{f'}$. The magnitude of this dynamic effect will vary across regions and years based on the initial distribution of fuel sets $Pr_{t-2}\left(\mathcal{F}' \mid z\right)$, the distribution of productivity across regions,$f\left(z\right)$, and all other factors that affect switching probabilities, such as input prices.

6.3.3 Input-output linkage

In a full-fledged model, we add an input-output linkage in the production function, which is important because heavy industry is dirtier than light industry and the former is, in general,

the upstream sector of the latter.

$$q^{n,j}\left(\mathcal{F},z\right)=z\left[\left(l^{n,j}\right)^{1-\xi^{n,j}-\zeta^{n,j}}\left(k^{n,j}\right)^{\xi^{n,j}}\left(e^{n,j}\left(\mathcal{F}\right)\right)^{\zeta^{n,j}}\right]^{\gamma^{n,j}}\prod_{k=1}^{J}\left(m^{n,kj}\right)^{\gamma^{n,kj}}$$

where $\gamma^{n,j}$ is the share of value added in production, $\gamma^{n,jk}$ are the corresponding input-output coefficients such that $\gamma^{n,j}+\sum_k\gamma^{n,jk}=1$. $m^{n,kj}$ denotes material from sector k to j in location n. Hence, the sectoral composite final good is consumed by local households and used as materials for the production of intermediate varieties (roundabout production). From the roundabout production, the price of material in n from industry k is given by $P^{n,k}$. Thus,

$$x^{n,j}\left(\mathcal{F}\right)=B^{n,j}\left[\left(w^{n,j}\right)^{1-\xi^{n,j}-\zeta^{n,j}}\left(r^{n,j}\right)^{\xi^{n,j}}\left(\tilde{p}^{n,j}\left(\mathcal{F}\right)\right)^{\zeta^{n,j}}\right]^{\gamma^{n,j}}\prod_{k}\left(P_t^{n,k}\right)^{\gamma^{n,kj}}$$

6.4 Aggregation and Market Clearing

First of all, we need to characterize $F_t^{n,j}\left(z\mid\mathcal{F}\right)$, which is the distribution of z given fuel set $\mathcal{F}$, location n, sector j,and time t. This cumulative distribution function will be an important endogenous object important in aggregation and equilibrium characterization. We use the Kolmogorov forward equation with the transition probability $\varphi_t\left(\mathcal{F}'\mid\mathcal{F},z\right)$ we derived and the AR(1) process of productivity $F_t^n\left(z\right)$ given exogenously. As a first step, we model the joint evolution of $\mathcal{F}$ and z by combining the Kolmogorov equation for the AR(1) process with the equation for the state transitions of $\mathcal{F}$. The joint probability evolves recursively

$$\begin{aligned}p_t\left(\mathcal{F},z\right)&=\sum_{\mathcal{F}'}\int\varphi_{t-1}\left(\mathcal{F}\mid\mathcal{F}',z'\right)\cdot p\left(z_t=z|\mathcal{F}_{t-1}=\mathcal{F}',z_{t-1}=z'\right)\cdot p_{t-1}\left(\mathcal{F}',z'\right)dz_{t-1}\\&=\sum_{\mathcal{F}'}\int\varphi_{t-1}\left(\mathcal{F}\mid\mathcal{F}',z'\right)\cdot p\left(z|z'\right)\cdot p_{t-1}\left(\mathcal{F}',z'\right)dz_{t-1}\end{aligned}$$

where $p_t\left(\mathcal{F},z\right)=p_t\left(\mathcal{F}_t=\mathcal{F},z_t=z\right)$ and $p\left(z_t=z|\mathcal{F}_{t-1}=\mathcal{F}',z_{t-1}=z'\right)=p\left(z_t|z_{t-1}\right)$ because z_t depends only on $z_{t=1}$. Note that $z_t|z_{t=1}\sim N\left(\mu^j+\mu^n+\rho z_{t=1},\sigma^2\right)$. Once we solve this equation and have the probability density function, we can derive a conditional probability.

$$p_t\left(z|\mathcal{F}\right)=\frac{p_t\left(\mathcal{F},z\right)}{p_t\left(\mathcal{F}\right)}$$

and compute the cumulative distribution function $F_t\left(z\mid\mathcal{F}\right)$

$$F_t\left(z\mid\mathcal{F}\right)=\int_{-\infty}^{z}p\left(x|\mathcal{F}\right)dx$$

Now, we prepare several equations to characterize a general equilibrium. Using (Equation 2), (Equation 3), and (Equation 7), we obtain the expected revenue of selling goods from n to i in sector j with fuel set $\mathcal{F}$.

$$R^{ni,j}\left(\mathcal{F}\right)=\int M^{n,j}\left(\mathcal{F},z\right)\left(zP^{i,j}\right)^{\sigma^{j}-1}\left(d^{ni,j}x^{n,j}\left(\mathcal{F},z\right)\right)^{1-\sigma^{j}}X^{i,j}dF^{n,j}\left(z\mid\mathcal{F}\right)$$

We assume that pollution tax revenues are lost to rent-seeking.

$$\begin{aligned}TR^{ni,j}\left(\mathcal{F}\right)&=\sum_{f}\int M^{n,j}\left(\mathcal{F},z\right)\tau^{n,f}e^{ni,j,f}\left(\mathcal{F},z\right)dF^{n,j}\left(z\mid\mathcal{F}\right)\\&=R^{ni,j}\left(\mathcal{F}\right)\sum_{f}\frac{\tau^{n,f}}{C^{n,j,f}}\end{aligned}$$

where $C^{n,j,f}=\frac{\sigma^{j}-1}{\sigma^{j}}\left(w^{n,j}\frac{1-\xi^{n,j}-\zeta^{n,j}}{\zeta^{n,j}}+r^{n,j}\frac{\xi^{n,j}}{\zeta^{n,j}}+\sum_{k=1}^{J}P^{n,k}\frac{\gamma^{n,kj}}{\gamma^{n,j}\zeta^{n,j}}+\sum_{f}\left(\tau^{n,f}+p^{f}\right)\right)\left(\sum_{f'}\left(\beta^{j,f'}\left(\frac{\tau^{n,f'}+p^{f'}}{\tau^{n,f}+p^{f}}\right)^{-\lambda}\left(\frac{\beta^{j,f'}}{\beta^{j,f}}\right)^{\lambda-1}\right)^{\frac{\lambda-1}{\lambda}}\right)^{\frac{\lambda}{\lambda-1}}$.

We define the expected revenue of selling goods from n to i in sector j with fuel set $\mathcal{F}$ net of pollution tax

$$X^{ni,j}\left(\mathcal{F}\right)=R^{ni,j}\left(\mathcal{F}\right)-TR^{ni,j}\left(\mathcal{F}\right)$$

Hence, any trade flows should net out such tax revenues. We denote by $\eta^{ni,j}\left(\mathcal{F}\right)$ the aggregate bilateral expenditure shares of goods purchased by i from n in sector j produced with fuel set $\mathcal{F}$.

$$\eta^{ni,j}\left(\mathcal{F}\right)=\frac{X^{ni,j}\left(\mathcal{F}\right)}{\sum_{h}\sum_{\mathcal{F}}X^{hi,j}\left(\mathcal{F}\right)}\tag{13}$$

$$\eta^{ni,j}=\sum_{\mathcal{F}\in\mathbb{F}}\eta^{ni,j}\left(\mathcal{F}\right)\tag{14}$$

The expenditure in location i and sector j is

$$X^{i,j}=\sum_{n}\sum_{\mathcal{F}}X^{ni,j}\left(\mathcal{F}\right)\tag{15}$$

Total income in location n and sector j is given by

$$I^{n,j}=w^{n,j}L^{n,j}+r^{n,j}K^{n,j}\tag{16}$$

The term on the right-hand side of this equation represents the income of the workers (payment to labor across all sectors). The total expenditure on goods in sector j and location n is given by the expenditure on materials from firms across all other sectors (input-output

linkages) and for final consumption, in order:

$$X^{n,j} = \sum_{k=1}^{N} \gamma^{n,kj} \sum_{i=1}^{N} \left(1 - 1/\sigma^{k}\right) \eta^{ni,k} X^{i,k} + \alpha^{n,j} I^{n,j} \tag{17}$$

for all location n and sector j where $\sum_{i=1}^{N} \left(1 - 1/\sigma^{k}\right) \eta^{ni,k} X^{i,k}$ is the value of gross output in sector k and location n.

The labor market clearing condition for each sector and region is given by

$$w^{n,j} L^{n,j} = \left(1 - \xi^{n,j} - \zeta^{n,j}\right) \gamma^{n,j} \sum_{i=1}^{N} \left(1 - 1/\sigma^{j}\right) \eta^{ni,j} X^{i,j} \tag{18}$$

for all location n and sector j.

The capital market clearing condition for each sector and region is given by

$$r^{n,j} K^{n,j} = \xi^{n} \sum_{j=1}^{J} \gamma^{n,j} \sum_{i=1}^{N} \left(1 - 1/\sigma^{j}\right) \eta^{ni,j} X^{i,j} \tag{19}$$

for all location n and sector j. Note that fuels are traded at world prices. Specifically, fuels are supplied at given prices indefinitely while they are demanded by intermediate good producers.

6.5 Equilibrium

The exogenous state of the economy is determined by the set of constant and time-varying fundamentals$\Theta_t = \left\{ \left\{ f^{\mathcal{F}\mathcal{F}'} \right\}_{\mathcal{F} \subseteq \mathbb{F}}, \left\{ d^{ni,j} \right\}_{n=1;i=1;j=1}^{N;N;J}, \left\{ F_t^{n,j}(z), L_0^{n,j}, K_0^{n,j} \right\}_{n=1;j=1}^{N;J}, \left\{ \beta^{j,f} \right\}_{j=1;f}^{J;\mathbb{F}}, \left\{ p_t^{f} \right\}_{f}^{\mathbb{F}} \right\}$. For notational convenience, we use bold letters to denote vectors. They are bilateral fuel-switching fixed costs, non-tariff (iceberg) trade costs, the distributions of productivity and fuel productivity across regions and sectors, and world fuel prices. We define by $\boldsymbol{\tau}_t \equiv \left\{ \tau_t^{n,f} \right\}_{n=1;f}^{N;F}$ the set of environmental policies across regions expressed as pollution taxes. The distribution of firms, $\boldsymbol{M}_t = \left\{ M_t^{n,j}(\mathcal{F}) \right\}_{n=1;j=1;\mathcal{F}}^{N;J;\mathbb{F}}$, summarizes the overall fuel set distribution of the economy.

Let us define the equilibrium firm transition rates at time t by $\boldsymbol{\varphi}_t = \left\{ \varphi_t^{nj}(\mathcal{F}'|\mathcal{F}, z) \right\}_{n=1;j=1;\mathcal{F}}^{N;J;\mathbb{F}}$ for z, the value function for the firms by $\boldsymbol{V}_t = \left\{ V_t^{n,j}(\mathcal{F}, z) \right\}_{n=1;j=1;\mathcal{F}}^{N;J;\mathbb{F}}$ for z, equilibrium wages by $\boldsymbol{w}_t = \left\{ w_t^{n,j} \right\}_{n=1;j=1}^{N;J}$, rental rates by $\boldsymbol{r}_t = \left\{ r_t^{n,j} \right\}_{n=1;j=1}^{N;J}$, fuel price by $\boldsymbol{p_t} = \left\{ p_t^{f} \right\}_{f}^{F}$, aggregate and bilateral expenditures $\boldsymbol{X_t} = \left\{ X_t^{ni,j} \right\}_{n=1;i=1;j=1}^{N;N;J}$ where $X_t^{ni,j}$ is the expenditure of goods by i on goods produced by n in sector j, that is $X_t^{ni,j} = \eta_t^{ni,j} X_t^{i,j}$, regional sectoral

prices by $\boldsymbol{P}_t = \left\{P_t^{n,j}\right\}_{n=1;j=1}^{N;J}$. We now define the general equilibrium of the model given a sequence of fundamentals and policies

Definition 1. *Given an initial allocation of firms with fuel sets $\boldsymbol{M}_0$, a sequence of fundamentals $\{\Theta_t\}_{t=0}^{\infty}$, and a sequence of policies $\{\boldsymbol{\tau}_t\}_{t=0}^{\infty}$, a* **general equilibrium** *of the model is a vector of wages, rental rates, and prices for final goods $\{\boldsymbol{w}_t, \boldsymbol{r}_t, \boldsymbol{P}_t\}_{t=0}^{\infty}$ and an allocation $\left\{\left\{e^{n,j,f}\left(\mathcal{F},z\right)\right\}_f, \ell^{n,j}\left(\mathcal{F},z\right), k^{n,j}\left(\mathcal{F},z\right), \left\{m^{n,kj}\left(\mathcal{F},z\right)\right\}_{k=1}^{J}\right\}_{n=1;j=1}^{N;J}$ for $(\mathcal{F},z)$ and $\{\boldsymbol{M}_t, \boldsymbol{\varphi}_t, \boldsymbol{V}_t, \boldsymbol{U}_t\}$ that solve the firm dynamic problem (Equation 9) and the static problems of the households and producers at each t, using equilibrium conditions (Equations 3, 5, 6, 7, 14, 16, and 12) and clears final good and factor markets(Equations 17, 18, and 19).*

Definition 2. *A stationary steady state of the economy is an equilibrium in which all endogenous variables are time invariant*

Note that plants switch their fuel sets over time even in this steady state because of the AR(1) process. What does not change is the conditional distribution of productivity $dF_t^{n,j}\left(z \mid \mathcal{F}\right) = dF^{n,j}\left(z \mid \mathcal{F}\right)$ (stationary distribution) and hence endogenous variables such as $\{\boldsymbol{M}_t, \boldsymbol{\varphi}_t, \boldsymbol{V}_t, \boldsymbol{U}_t\}$.

Proposition 1. *Existence a unique steady-state (up to scale)*

Proof. Use results from Kleinman, E. Liu, and Redding (2023), show that the spectral radius of the matrix of elasticities of the nonlinear system at the steady state is equal to 1.

7 Model Solution

The primary goal of the model is to assess the impact of environmental policy on long run emissions, output, and hence welfare in aggregate and across regions. We solve for a rational expectation general equilibrium, beginning with the economy calibrated to the 2016 data, and simulating forward until the economy reaches a steady state. For implementation, we choose $J = 2$ where there are heavy and light industries.

7.1 Model solution

7.1.1 Steady State

1. This is a hypothetical steady state we target in counterfactuals.

2. We are given the initial allocation of the number of firms with specific fuel sets and the set of fundamentals as well as parameters calibrated or estimated

3. Given a guess on prices $\{\boldsymbol{w}_t, \boldsymbol{r}_t, \boldsymbol{P}_t\}_{t=0}^{\infty}$, firms and households solve their optimization problem

   (a) Guess $\boldsymbol{M}_t$

   (b) Firm optimization

      i. Guess $\{X^{n,j}\}$ and solve for $\{X^{n,j}\}$ using Equation 15

      ii. Update $\{X^{n,j}\}$ until convergence

      iii. Solve for the dynamic fuel set choice problem in Equation 9 until convergence

   (c) Update $\boldsymbol{M}_t$ using Equation 12 until convergence

   (d) Find a stationary distribution

      i. Guess a distribution for the state space

      ii. Use the policy function derived above to update the guess

      iii. If they converge, keep the distribution and move on

      iv. Otherwise, use this new distribution as a new guess and repeat till convergence

   (e) Update $\{\boldsymbol{P}_t\}_{t=0}^{\infty}$ until convergence

   (f) If labor markets clear, keep $\{\boldsymbol{w}_t\}_{t=0}^{\infty}$

   (g) Otherwise, update and go back to Step 3.

   (h) If capital markets clear, keep $\{\boldsymbol{r}_t\}_{t=0}^{\infty}$

   (i) Otherwise, update and go back to Step 3.

4. Household income (consumption), static production, and emissions can be derived

7.1.2 Transition

8 Calibration and Estimation

We calibrate a set of parameters using data and those from the literature. Table 4 summarizes the values and the sources or the methods of the calibration.

Table 4: Calibrated Parameters

Parameters	Name	Value	Source or Method
p_t^f	Fuel prices		Our World In Data
$d^{ni,j}$	Iceberg trade cost between n and i in sector j		Arkolakis and Walsh (2024) and data
β	Discount factor	1/1.05	No growth in a long run steady state
$L_0^{n,j}$	Regional and sectoral labor endowment		Data
$K_0^{n,j}$	Regional and sectoral capital endowment		Data
Υ	Social cost of carbon		Shapiro (2016), IPCC

Note. IPCC stands for Intergovernmental Panel on Climate Change.

8.1 Production Function

We separate the production function estimation in this section as it is one of the key contributions of this paper. We propose a three-stage estimation strategy following Murray Leclair (2024). Upon estimation, we should have everything necessary to characterize several key elasticities of interest and quantitatively study the implication of spatially differentiated environmental policies.

8.1.1 Stage 1: Outer Production Function — Calibration

To be consistent with the production function estimation literature, we discretize the model and index individual firms by subscript s. Thus, the output of a given firm s in location n and industry j and region i is:

$$q_{st} = \left[(l_{st})^{1-\xi^{n,j}-\zeta^{n,j}} (k_{st})^{\xi^{n,j}} (e_{st})^{\zeta^{n,j}} \right]^{\gamma^{n,j}} \prod_{k=1}^{J} \left(m_{st}^k\right)^{\gamma^{n,kj}} z_{st} e^{\epsilon_{st}},$$

where $z_{st}$is analogous to productivity z in previous sections and $e^{\epsilon_{st}}$ is an ex-post productivity shock, which is realized after the firm makes production decisions. While the quantity of energy e_{st} is unobserved, the profit maximization implies that firm-level energy spending is equal to observed firm-level fuel spending: $\mathcal{S}_{st}^e = \sum_{f \in \mathcal{F}} \mathcal{S}_{st}^f$. We calibrate the Cobb-Douglas input shares using sector and region expenditure shares, but we estimate everything else. This could be relaxed, and identification will go through similarly to Fan, Lee, and Smeets, 2022. Let $\mathcal{S}_t^x(\omega)$ be the observed firm-level spending on input x. Let $S_{st}^{va} = \mathcal{S}_{st}^e + \mathcal{S}_{st}^k + \mathcal{S}_{st}^l$ be the observed firm-level spending on all non-material (value-added) inputs. Then, the Cobb-Douglas shares can be calibrated as

$$\begin{aligned}
\hat{\zeta}^{n,j} &= \frac{\sum_t \sum_s \mathcal{S}^e_{st}}{\sum_t \sum_s \mathcal{S}^{va}_{st}} \\
\hat{\xi}^{n,j} &= \frac{\sum_t \sum_s \mathcal{S}^k_{st}}{\sum_t \sum_s \mathcal{S}^{va}_{st}} \\
1 - \hat{\gamma}^{n,j} &= \frac{\sum_t \sum_s \mathcal{S}^m_{st}}{\sum_t \sum_s \left(\mathcal{S}^{va}_{st} + \mathcal{S}^m_{st}\right)}
\end{aligned} \tag{20}$$

where $\gamma^{n,kj}$ is taken from regional input-output tables because we only observe the total material input at the firm-level.

Recalling that there are only two industries (light and heavy industries) and we are assuming constant returns to scale, we have $\hat{\gamma}^{n,kj} + \hat{\gamma}^{n,jk} = 1 - \hat{\gamma}^{n,j}$.

8.1.2 Stage 2: Inner Production Function (Energy) — Estimation

To estimate productivity, demand-side parameters, and parameters of the energy production function, we expand the energy choice of firms:

$$e_{st} = \left(\left(\sum_{f \in \mathcal{F}_{st}} \beta^{j,f} \left(\mathcal{F}_{st}\right) \left(e^f_{st}\right)^{\frac{\lambda^j - 1}{\lambda^j}} \right)^{\frac{\lambda^j}{\lambda^j - 1}} \right)^{\zeta^{n,j}}$$

The goal is now to estimate the elasticity of demand σ^j, the inter-fuel elasticity of substitution λ^j , average fuel-specific distribution efficiency parameter $\beta^{n,j}$, and to recover firm-level productivity $z_t(\omega)$. Since we do not observe firm-level output prices, we show an approach that relies on firm-level revenue and optimality conditions to recover both production parameters and the demand elasticity. This approach exploits the first-order conditions of profit maximization to address the simultaneity bias coming from productivity and input choices, which is similar to the approach taken by Gandhi, Navarro, and Rivers (2020), Grieco, Li, and Zhang (2016), Doraszelski and Jaumandreu (2013), and many others. Our particular approach leverages the fact that markups are constant and directly map into the elasticity of demand. Let us start by defining total firm-level revenues from the demand side, which is the sum of revenues from selling to all regions, and using Equation 2

$$
\begin{aligned}
\mathcal{R}_{st} &= \sum_i p_{st}^{ni,j} q_{st}^{ni,j} \\
&= \sum_i \left[\left(q_{st}^{ni,j}\right)^{\left(\sigma^j-1\right)/\sigma^j} \left(\frac{X_t^{i,j}}{\left(P_t^{i,j}\right)^{1-\sigma^j}} \right)^{1/\sigma^j} \right] \\
&= \left(q_{st}\right)^{\left(\sigma^j-1\right)/\sigma^j} \sum_i \left[\left(r_{st}^{ni,j}\left(\omega\right)\right)^{\left(\sigma^j-1\right)/\sigma^j} \left(\frac{X_t^{i,j}}{\left(P_t^{i,j}\right)^{1-\sigma^j}} \right)^{1/\sigma^j} \right]
\end{aligned}
$$

where total quantity manufactured by the firm can also be written as $q_{st} \equiv \sum_i d^{ni,j} q_{st}^{ni,j} e^{\epsilon_{st}}$. We define $r_{st}^{ni,j} = q_{st}^{ni,j} e^{\epsilon_{st}} / q_{st}$ as the firm-level ratio of output sold in region i relative to total output manufactured. It can be shown that this share of output only depends on iceberg trade costs and local market conditions across all destinations. See appendix. It plays a similar role as productivity as it scales up and down total output manufactured, but is independent of relative input choices. Using Equation 7, we show that conditional on location and industry, this output destination share does not vary across firms:

$$
r_{st}^{ni,j} = \frac{\left(P_t^{i,j}\right)^{\sigma^j-1} X_t^{i,j} \left(d^{ni,j}\right)^{-\sigma^j}}{\sum_i \left(P_t^{i,j}\right)^{\sigma^j-1} X_t^{ij} \left(d^{ni,j}\right)^{1-\sigma^j}} = r_t^{ni,j}.
$$

Then, the firm-level revenue can be rewritten as a function of total output manufactured q_{st} and a function of local market conditions $\Gamma_t^{n,j} = \sum_i \left[\left(\tilde{q}_t^{ni,j}\right)^{\left(\sigma^j-1\right)/\sigma^j} \left(\frac{X_t^{i,j}}{\left(P_t^{i,j}\right)^{1-\sigma^j}} \right)^{1/\sigma^j} \right] = \left(\sum_i \left(d^{ni,j}\right)^{1-\sigma^j} X_t^{i,j} \left(P_t^{i,j}\right)^{\sigma^j-1} \right)^{\frac{1}{\sigma^j}}$ that is common across all firms producing in region n and sector j. Then, we can redefine firm-level revenues into a standard expression, in which all trade frictions

$$
\begin{aligned}
\mathcal{R}_{st} &= \left(q_{st}\right)^{\left(\sigma^j-1\right)/\sigma^j} \Gamma_t^{n,j} && (21) \\
&= \left(\tilde{q}_{st}\right)^{\left(\sigma^j-1\right)/\sigma^j} \Gamma_t^{n,j} e^{u_{st}} && (22)
\end{aligned}
$$

where $e^{u_{st}} \equiv e^{\frac{\sigma^j-1}{\sigma^j}\epsilon_{st}}$ is an ex-post shock to revenues (from the ex-post productivity shock) and $\tilde{q}_{st}$ is the firm's planned output. Using this formulation, we can write the static profit maximization problem of the firm as a single optimization problem. We leverage the fact that one fuel is used by all firms (electricity) to get an estimating equation.

$$\pi_{st}^{n,j} = \max_{l_{st},k_{st},\left\{e_{st}^{f}\right\}_{f\in\mathcal{F}_{st}},\left\{m_{st}^{k}\right\}_{k=1}^{J}} \left\{ \left(\tilde{q}_{st}\right)^{\left(\sigma^{j}-1\right)/\sigma^{j}} \Gamma_{t}^{n,j} - w_{t}^{n,j} l_{st} - r_{t}^{n,j} k_{st} - \sum_{f\in\mathcal{F}_{st}} \left(p_{t}^{f} + \tau_{t}^{n,f}\right) e_{st}^{f} \right\}$$

$$s.t.\ \tilde{q}_{st} = z_{st} \left[\left(l_{st}\right)^{1-\xi^{n,j}-\zeta^{n,j}} \left(k_{st}\right)^{\xi^{n,j}} \left(\left(\sum_{f\in\mathcal{F}_{st}} \beta^{j,f}\left(\mathcal{F}_{st}\right) \left(e_{st}^{f}\right)^{\frac{\lambda^{j}-1}{\lambda^{j}}} \right)^{\frac{\lambda^{j}}{\lambda^{j}-1}} \right)^{\zeta^{n,j}} \right]^{\gamma^{n,j}} \prod_{k=1}^{J} \left(m_{st}^{k}\right)^{\gamma^{n,kj}}$$

Now take the first-order condition with respect to a fuel f' that is in every fuel set (e.g., electricity). Let $\overline{q}_{st} \equiv \tilde{q}_{st}/z_{st}$ be defined as planned output net of productivity. Then,

$$\frac{\sigma^{j}-1}{\sigma^{j}} \left(z_{st}\right)^{\frac{\sigma^{j}-1}{\sigma^{j}}} \left(\overline{q}_{st}\right)^{\frac{\sigma^{j}-1}{\sigma^{j}}} \Gamma_{t}^{n,j} \frac{\zeta^{n,j}\gamma^{n,j}\beta^{j,f'}\left(\mathcal{F}_{st}\right)\left(e_{st}^{f'}\right)^{-1/\lambda^{j}}}{\sum_{f\in\mathcal{F}_{st}}\beta^{j,f}\left(\mathcal{F}_{st}\right)\left(e_{st}^{f}\right)^{\frac{\lambda^{j}-1}{\lambda^{j}}}} = p_{t}^{f'} + \tau_{t}^{n,f'}. \tag{23}$$

We can then solve for productivity and rearrange terms, where $\mathcal{S}_{st}^{f'} = \left(p_{t}^{f'} + \tau_{t}^{n,f'}\right) e_{st}^{f'}$ is defined as the firm-level spending on electricity

$$\left(z_{st}\right)^{\frac{\sigma^{j}-1}{\sigma^{j}}} = \frac{\sigma^{j}}{\sigma^{j}-1} \frac{1}{\Gamma_{t}^{n,j}} \left(\overline{q}_{st}\right)^{\frac{1-\sigma^{j}}{\sigma^{j}}} \frac{\mathcal{S}_{st}^{f'} \sum_{f\in\mathcal{F}_{st}} \beta^{j,f}\left(\mathcal{F}_{st}\right)\left(e_{st}^{f}\right)^{\frac{\lambda^{j}-1}{\lambda^{j}}}}{\zeta^{n,j}\gamma^{n,j}\beta^{j,f'}\left(\mathcal{F}_{st}\right)\left(e_{st}^{f'}\right)^{\frac{\lambda^{j}-1}{\lambda^{j}}}} \tag{24}$$

We now plug this productivity term (Equation 24) into the revenue (Equation 21), and rearrange to get the following estimating equation that identifies all production function parameters

$$\begin{aligned}
\mathcal{R}_{st} =& \left[\left(z_{st}\right)^{\frac{\sigma^{j}-1}{\sigma^{j}}} \left(\overline{q}_{st}\right)^{\frac{\sigma^{j}-1}{\sigma^{j}}} \right] \Gamma_{t}^{n,j} e^{u_{st}} \\
=& \frac{\sigma^{j}}{\sigma^{j}-1} \frac{\mathcal{S}_{st}^{f'} \sum_{f\in\mathcal{F}_{st}} \beta^{j,f}\left(\mathcal{F}_{st}\right)\left(e_{st}^{f}\right)^{\frac{\lambda^{j}-1}{\lambda^{j}}}}{\zeta^{n,j}\gamma^{n,j}\beta^{j,f'}\left(\mathcal{F}_{st}\right)\left(e_{st}^{f'}\right)^{\frac{\lambda^{j}-1}{\lambda^{j}}}} e^{u_{st}} \\
=& \frac{\sigma^{j}}{\sigma^{j}-1} \frac{\mathcal{S}_{t}^{n,j,f'}}{\zeta^{n,j}\gamma^{n,j}} \left(1 + \sum_{f\in\mathcal{F}_{st}\setminus f'} \frac{\beta^{j,f}\left(\mathcal{F}_{st}\right)}{\beta^{j,f'}\left(\mathcal{F}_{st}\right)} \left(\frac{e_{st}^{f}}{e_{st}^{f'}}\right)^{\frac{\lambda^{j}-1}{\lambda^{j}}} \right) e^{u_{st}}
\end{aligned}$$

To get an estimating equation in firm-level revenues, we define revenues relative to known objects s.t. $\tilde{\mathcal{R}}_{st} \equiv \mathcal{R}_{st} \frac{\hat{\zeta}^{n,j}\hat{\gamma}^{n,j}}{\mathcal{S}_{st}^{f'}}$

$$\ln \tilde{R}_{st} = \ln\left(\frac{\sigma^j}{\sigma^j - 1}\right) + \ln\left(1 + \sum_{f \in \mathcal{F}_{st} \setminus f'} \frac{\beta^{j,f}\left(\mathcal{F}_{st}\right)}{\beta^{j,f'}\left(\mathcal{F}_{st}\right)} \left(\frac{e_{st}^f}{e_{st}^{f'}}\right)^{\frac{\lambda^j - 1}{\lambda^j}}\right) + u_{st} \tag{25}$$

Under the assumption $\sum_{f \in \mathcal{F}} \beta^{j,f}\left(\mathcal{F}\right) = 1$, the elasticity of demand is identified as a constant due to the constant markup scaling up revenues for all firms. All parameters of the energy production function are identified from variation in observed relative fuel quantities, which are independent of the ex-post shock to revenues and firm-level productivity (because it shifts input quantities up and down proportionally). Grieco, Li, and Zhang (2016) show formal identification results for a very similar model. We can estimate all production parameters along with the elasticity of demand using a non-linear least squares estimator (NLLS).

8.1.3 Stage 3: Estimating Fuel Set Switching Costs

In this stage, we estimate the cost of switching fuel sets. To do this, we must simulate counterfactual profits under different fuel sets. That require us to recover fuel (pollution taxes) and firm-level productivity.

Recovering Pollution (Fuel)Tax (Work in Progress) **Model-free version** In the data, we observe each firm's each fuel use $\left\{e_{st}^f\right\}_{f \in \mathcal{F}_{st}}$ in tons of oil equivalent (TOE). We observe regional spending on all non-electricity fuels combined $\mathcal{S}_{st}^{fossil} = \sum_{f \in \mathcal{F}_{st} \setminus elec} \left(p_t^f + \tau_t^{n,f}\right) e_{st}^f$, and firm-level spending on electricity $\mathcal{S}_{st}^{elec} = \left(p_t^{elec} + \tau_t^{n,elec}\right) e_{st}^{elec}$. For electricity, we can recover a firm-specific electricity price p_{st}^{elec}, which we average to get annual regional electricity prices: $p_t^{n,elec}$. For the other fuels, we show below how to recover regional fuel prices directly $p_t^{n,f}$. We can then separate this price into a world spot market price (observed) and a shadow price (regional pollution tax):

$$p_t^{n,f} = \underbrace{p_t^f}_{\text{World spot price}} + \underbrace{\tau_t^{n,f}}_{\text{Fuel (pollution) tax}}$$

We can recover these regional fuel prices by looking at variations in fuel spending and quantity across firms within region-year pairs, where $e_{st}^f = 0$ if $f \notin \mathcal{F}_{st}$ (firm s is not using fuel f). For firms $s = 1, .., S$ and fuels $f = 1, ..., F$ in region n,

$$\begin{bmatrix} s_{1t}^{fossil} \\ \vdots \\ s_{St}^{fossil} \end{bmatrix} = \begin{bmatrix} e_{1t}^{f=1} & \dots & e_{1t}^{f=F} \\ \vdots & \ddots & \vdots \\ e_{St}^{f=1} & \cdots & e_{St}^{f=F} \end{bmatrix} \begin{bmatrix} p_t^{n,f=1} \\ \vdots \\ p_t^{n,f=F} \end{bmatrix}$$
$$\Leftrightarrow \mathbf{s}_t^n = \mathbf{e}_t^n \mathbf{p}_t^n$$

Note that the matrix of fuel quantities does not contain electricity. Then, since the number of firms outnumbers the number of fuels $M >> F$, we can find the price vector that minimizes the squared residuals, $||\mathbf{s}_t^n - \mathbf{e}_t^n \mathbf{p}_t^n||^2$, which yields a OLS formula for the price vector, $\hat{\mathbf{p}}_t^n = (\mathbf{e}_t^{n\prime}\mathbf{e}_t^n)^{-1}(\mathbf{e}_t^{n\prime}\mathbf{s}_t^n)$. We can easily get this price vector by regressing fuel quantities on fuel spending without a constant, separately by region and year. Further, with world fuel prices, p_t^f, we recover pollution taxes across regions and years. Given the world fuel prices p_t^f, we recover shadow prices directly s.t. $\hat{\tau}_t^{n,f} = \hat{p}_t^{n,f} - p_t^f$.

Recovering Productivity First, we can rewrite market aggregates when productivity varies across firms (indexed by s).

$$\begin{aligned} P_t^{n,j} &= \left(\sum_{i=1}^{N} \int_{\Omega^{i,j}} \left(p_t^{in,j}(\omega) \right)^{1-\sigma^j} d\omega \right)^{\frac{1}{1-\sigma^j}} \\ &= \left(\sum_{i=1}^{N} \sum_{s} \left(p_{st}^{in,j} \right)^{1-\sigma^j} \right)^{\frac{1}{1-\sigma^j}} \\ &= \left(\frac{\sigma^j}{\sigma^j - 1} \right) \left(\sum_{i} \left(d^{in,j} \right)^{1-\sigma^j} \sum_{\mathcal{F}} \sum_{s} \left(\frac{x_t^{i,j}(\mathcal{F}_{st})}{z_{st}} \right)^{1-\sigma^j} \right)^{\frac{1}{1-\sigma^j}} \end{aligned}$$

We then get a definition of productivity from firms' first-order conditions with respect to electricity (Equation 23)

$$\underbrace{z_{st}}_{\text{Productivity (unobserved)}} = \underbrace{\ln \hat{\Omega}_{st}}_{\text{Production (observed)}} - \underbrace{\ln \tilde{\Gamma}_t^{n,j}}_{\text{Demand (unobserved)}}$$

where $\hat{\Omega}_{st} = \left(\frac{\hat{\sigma}^j}{\hat{\sigma}^j - 1} \left((l_{st})^{1-\hat{\xi}^{n,j}-\hat{\zeta}^{n,j}} (k_{st})^{\hat{\xi}^{n,j}} (\hat{e}_{st})^{\hat{\zeta}^{n,j}} \right)^{\frac{1-\hat{\sigma}^j}{\hat{\sigma}^j}} \frac{\mathcal{S}_{st}^{elec} \sum_{f \in \mathcal{F}_{st}} \hat{\beta}^{j,f}(\mathcal{F}_{st}) \left(e_{st}^f \right)^{\frac{\hat{\lambda}^j - 1}{\hat{\lambda}^j}}}{\hat{\zeta}^{n,j} \hat{\gamma}^{n,j} \hat{\beta}^{j,elec}(\mathcal{F}_{st}) \left(e_{st}^{elec} \right)^{\frac{\hat{\lambda}^j - 1}{\hat{\lambda}^j}}} \right)^{\frac{\hat{\sigma}_j}{\hat{\sigma}_{j-1}}}$ is a function of production parameters (and is roughly proportional to output), which are all

recovered at this stage. Assuming that productivity follows an AR(1) process with industry and region fixed effects s.t. $z_{st} = (1-\rho)(\mu^n + \mu^j) + \rho z_{st-1} + \nu_{st}$, we can rearrange the definition of productivity above to get an estimating equation

$$\begin{aligned} \ln \hat{\Omega}_{st} - \rho \ln \hat{\Omega}_{st-1} &= (1-\rho)\left(\mu^n + \mu^j\right) + \ln \tilde{\Gamma}_t^{n,j} - \rho \ln \tilde{\Gamma}_{t-1}^{n,j} + \nu_{st} \\ &= \alpha_t^{n,j} + \nu_{st} \end{aligned} \tag{26}$$

which is a standard dynamic panel regression. ν_{st} is a shock to productivity between $t-1$ and t. $\ln \hat{\Omega}_{st-1}$ is correlated with ν_{st} because it is a function of past shocks. However, this a canonical dynamic panel, and ρ can be consistently estimated following the system GMM approach of Blundell and Bond (2000, 1998). $\alpha_t^{n,j} \equiv (1-\rho)(\mu^n + \mu^j) + \ln \tilde{\Gamma}_t^{n,j} - \rho \ln \tilde{\Gamma}_{t-1}^{n,j}$ can be estimated jointly with year fixed effects interacted with industry and regions.

To get an estimate of productivity, we need to separate $\ln \tilde{\Gamma}_t^{n,j}$ from $\ln \tilde{\Gamma}_{t-1}^{n,j}$ and fixed effects. However, we only get an estimate of the difference. There is one degree of underidentification, so we need to normalize one of the fixed effects. In other words, we have an initial condition problem**.** Since we know the definition of $\tilde{\Gamma}_t^{n,j}$, we can investigate conditions that give identification:

$$\tilde{\Gamma}_t^{n,j} = \left(\sum_i \left(d^{ni,j}\right)^{1-\sigma^j} X_t^{i,j} \left(P_t^{i,j}\right)^{\sigma^j - 1} \right)^{\frac{1}{\sigma^j - 1}}$$

where $d^{ni,j}$ are iceberg trade costs and are known at this stage. $X_t^{i,j}$ is known from the data (total sales in region i from industry j). However, the aggregate wholesale price index $P_t^{n,j} = \left(\frac{\sigma^j}{\sigma^j - 1}\right) \left(\sum_i \left(d^{in,j}\right)^{1-\sigma^j} \sum_{\mathcal{F}} \left(x_t^{i,j}(\mathcal{F})\right)^{1-\sigma^j} \sum_s^{M_t^{i,j}(\mathcal{F})} \left(z_{st}\right)^{\sigma^j - 1} \right)^{\frac{1}{1-\sigma^j}}$ in region n and industry j is unobserved. We take two approaches to identification of productivity.

Approach 1 (temporary): assuming frictionless inter-regional trade

If we assume that there are no trade frictions across regions s.t. $d^{in,j} = 1$, then the wholesale price index and aggregate demand factors are constant across regions

$$P_t^j = \left(\frac{\sigma^j}{\sigma^j - 1}\right) \left(\sum_i \sum_{\mathcal{F}} \left(x_t^{i,j}(\mathcal{F})\right)^{1-\sigma^j} \sum_s^{M_t^{i,j}(\mathcal{F})} \left(z_{st}\right)^{\sigma^j - 1} \right)^{\frac{1}{1-\sigma^j}}$$

$$\tilde{\Gamma}_t^j = \left(\sum_i X_t^{i,j} \left(P_t^j\right)^{\sigma^j - 1} \right)^{\frac{1}{\sigma^j - 1}}$$

In that case, we can recover $\tilde{\Gamma}_t^j$ directly from aggregate industry price indices. Once that is done, we can construct estimates of productivity directly as $z_{st} = \ln \hat{\Omega}_{st} - \ln \tilde{\Gamma}_t^j$.

Approach 2: recovering price indices directly using credit card data

As a permanent alternative, we are working on compiling transaction data from the Shinhan Bank to construct aggregate price indices that vary across industry. This data is only available for 2020 onwards. As long as we observe aggregate prices for at least two subsequent periods (e.g., 2020 and 2021), we can rely on the AR(1) assumption to recover productivity for all years. We need one year to deal with the initial condition and another year to deal with industry and region fixed effects. Say we can construct aggregate price indices for year t and $t+1$. Then, we can construct $\tilde{\Gamma}_t^{n,j}$ and $\tilde{\Gamma}_{t+1}^{n,j}$ directly. This way, we can recover industry and region fixed effects:

$$\ln \hat{\Omega}_{st+1} - \rho \ln \hat{\Omega}_{st} - \left(\ln \tilde{\Gamma}_{t+1}^{n,j} - \rho \ln \tilde{\Gamma}_t^{n,j} \right) = (1-\rho) \left(\mu^n + \mu^j \right) + \nu_{st}$$

Once we have estimates of fixed effects $\hat{\mu}^n$and $\hat{\mu}^j$(and $\hat{\rho}$ which we recovered in the first section), we can do the opposite of the last step by putting them on the left-hand-side. Starting from t and $t-1$, we can recover $\ln \tilde{\Gamma}_{t-1}^{n,j}$ because we observe $\ln \tilde{\Gamma}_t^{n,j}$ and so on and so forth.

$$\ln \hat{\Omega}_{st} - \rho \ln \hat{\Omega}_{st-1} - (1-\hat{\rho}) \left(\hat{\mu}^n + \hat{\mu}^j \right) = \left(\ln \tilde{\Gamma}_t^{n,j} - \rho \ln \tilde{\Gamma}_{t-1}^{n,j} \right) + \nu_{st}$$

Recovering Profits Once we have productivity estimates, we can recover firm-level static profits (inclusive of the ex-post productivity shock $e^{\epsilon_{st}}$), which will be used in the dynamic discrete choice model to estimate fixed switching costs between fuel sets.

$$\pi_{st} = \left(\Gamma_t^{n,j} \right)^{\sigma^j} \left(\frac{z_{st}}{x_t^{n,j}\left(\mathcal{F}_{st}\right)} \right)^{\sigma^j - 1} \left[\left(\frac{\sigma^j - 1}{\sigma^j} \right)^{\sigma^j - 1} e^{\epsilon_{st}(\sigma^j - 1)/\sigma^j} - \left(\frac{\sigma^j - 1}{\sigma^j} \right)^{\sigma^j} e^{\epsilon_{st}} \right]$$

where $x_t^{nj}\left(\mathcal{F}_{st}\right)$ is the unit cost function (Equation 6).

Estimating Fixed Costs

To estimate fixed costs to swtich between fuel sets, we assume that firms do not forecast input prices and regulation (they expect to keep facing the same prices forever), but they forecast their own productivity, which evolves according to a stationary Markov chain based on the AR(1) assumption. For now we treat the ex-post productivity shock $e^{\epsilon_{st}}$ as a measurement error such that firm-level expected profits do not depend on it, but this can

be relaxed later[5]. Under these assumptions, we can rewrite the expected value function in a recursive form and a fuel set-specific probability. Using Equations 10 and 11, we have that a firm with productivity e^{ε} and fuel set $\mathcal{F}$ has the following expected value function

$$V_t^{n,j}(\mathcal{F}, z) = \gamma + \pi_t^{n,j}(\mathcal{F}, z) + \vartheta \ln\Big(\sum_{\mathcal{F}' \subseteq \mathbb{F}} \exp\left(\beta \mathbb{E}_t^z \left[V_{t+1}^{nj}(\mathcal{F}', z') \mid \mathcal{F}, z\right] - f^{\mathcal{F}\mathcal{F}'}\right)^{\frac{1}{\vartheta}} \Big) \tag{27}$$

for all $\mathcal{F} \in \mathbb{F}$. Similarly, we get choice-specific probabilities as

$$\varphi_t^{n,j}\left(\mathcal{F}' | \mathcal{F}, z\right) = \frac{\exp\left(\beta \mathbb{E}_t^z \left[V_{t+1}^{n,j}(\mathcal{F}', z') \mid \mathcal{F}, z\right] - f^{\mathcal{F}\mathcal{F}'}\right)^{\frac{1}{\vartheta}}}{\sum_{\mathcal{F}'' \subseteq \mathbb{F}} \exp\left(\beta \mathbb{E}_t^z \left[V_{t+1}^{n,j}(\mathcal{F}', z') \mid \mathcal{F}, z\right] - f^{\mathcal{F}\mathcal{F}''}\right)^{\frac{1}{\vartheta}}}$$

for all $\mathcal{F} \in \mathbb{F}$. We can then write the individual likelihood for a set of parameters $\theta = \left(\left\{f^{\mathcal{F}\mathcal{F}'}\right\}, \vartheta\right)$ given some observed data $y_{st} = (z_{st}, \mathcal{F}_{st+1})$ as

$$\begin{aligned}
\mathcal{L}_t(\theta; y_{st}) &= \prod_{\mathcal{F} \subseteq \mathbb{F}} Pr_t^{nj}(\mathcal{F}', z' \mid z_{st-1}, \mathcal{F}_{st}; \theta)^{\mathbb{I}\{\mathcal{F}_{st+1} = \mathcal{F}', z_{st} = z'\}} \\
&= Pr_t^{n,j}(\mathcal{F}_{st+1}, z_{st} \mid z_{st-1}, \mathcal{F}_{st}; \theta)
\end{aligned}$$

Given the AR(1) assumption on productivity and the timing of firms' decisions, we get that the evolution of firm-level productivity is independent (log separable) of the fuel set that firms are using. This is a standard conditional independence assumption.[6] In that case, the individual likelihood collapse to:

$$\mathcal{L}_t(\theta; y_{st}) = \varphi_t^{n,j}(\mathcal{F}_{st+1} \mid \mathcal{F}_{st}, z_{st}; \theta)\, Pr_t^{n,j}(z_{st} \mid z_{st-1}; \theta)$$

The aggregate log-likelihood is defined as

$$\ln \mathcal{L}(\theta; \mathbf{y}) = \sum_s \sum_t \ln \varphi_t^{n,j}(\mathcal{F}_{st+1} \mid \mathcal{F}_{st}, z_{st}; \theta) + \sum_s \sum_t \ln Pr_t^{n,j}(z_{st} \mid z_{st-1}; \theta)$$

The state transition for productivity is estimated separately from the AR(1) regression

[5] If we include ex-post productivity shocks, we have to add an additional state variable. While these shocks appear after firms make production decisions, the distribution of these shocks does in principle matter for dynamic fuel set decisions.

[6] This is an important distinction from the cross-sectional distribution of productivity at any given time. Indeed, firms' choice of fuel set depends on their productivity (not the other way around), so the cross-sectional distribution of productivity is a function of the distribution of fuel sets in the economy.

above, so we can abstract from it in the likelihood. The literature on dynamic discrete choice model proposes various ways to maximize the likelihood. The most straightforward is the nested-fixed point algorithm (Rust, 1987). Another approach is the conditional choice probability (CCP) following Hotz and Miller (1993).

Estimating with conditional choice probability Leveraging the insight of Hotz and Miller (1993), we can estimate the fixed cost of switching fuel sets without explicitly solving for the fixed point, which has multiple computational advantages. To see this, we can slightly reorganize the expected value function

$$
\begin{aligned}
V_t^{n,j}(\mathcal{F}, z) &= \gamma + \pi_t^{nj}(\mathcal{F}, z) + \vartheta \ln\left(\sum_{\mathcal{F}' \subseteq \mathbb{F}} \exp\left(\beta \mathbb{E}_t^z\left[V_{t+1}^{n,j}\left(\mathcal{F}', z'\right) \mid \mathcal{F}, z\right] - f^{\mathcal{F}\mathcal{F}'}\right)^{\frac{1}{\vartheta}}\right) \\
&= \gamma + \pi_t^{nj}(\mathcal{F}, z) + \vartheta \ln\left(\sum_{\mathcal{F}' \subseteq \mathbb{F}} \exp\left(\bar{V}_t^{n,j,\mathcal{F}'}(\mathcal{F}, z)\right)^{\frac{1}{\vartheta}}\right) \\
&= \gamma + \pi_t^{nj}(\mathcal{F}, z) + \vartheta \ln\left(\frac{\sum_{\mathcal{F}'' \subseteq \mathbb{F}} \exp\left(\bar{V}_t^{n,j,\mathcal{F}''}(\mathcal{F}, z)\right)^{\frac{1}{\vartheta}}}{\exp\left(\bar{V}_t^{n,j,\mathcal{F}'}(\mathcal{F}, z)\right)^{\frac{1}{\vartheta}}} \exp\left(\bar{V}_t^{n,j,\mathcal{F}'}(\mathcal{F}, z)\right)^{\frac{1}{\vartheta}}\right) \\
&= \gamma + \pi_t^{nj}(\mathcal{F}, z) + \vartheta \ln\left(\frac{1}{\varphi_t^{nj}(\mathcal{F}' \mid \mathcal{F}, z)} \exp\left(\bar{V}_t^{n,j,\mathcal{F}'}(\mathcal{F}, z)\right)^{\frac{1}{\vartheta}}\right)
\end{aligned}
$$

where $\bar{V}_t^{n,j,\mathcal{F}'}(\mathcal{F}, z) = \beta \mathbb{E}_t^z\left[V_{t+1}^{n,j}\left(\mathcal{F}', z'\right) \mid \mathcal{F}, z\right] - f^{\mathcal{F}\mathcal{F}'}$ denotes fuel-set-specific value functions. We use the definition of choice probabilities φ. The key is that these choice probability $\varphi_t^{nj}(\mathcal{F}' \mid \mathcal{F}, z)$ can be directly recovered from the data (e.g., grouping fuel set transition shares by productivity bins). Using this formulation of the expected value function, we can then rewrite the choice-specific value function as

$$
\begin{aligned}
\bar{V}_t^{nj\mathcal{F}'}(\mathcal{F}, z) &= \beta \mathbb{E}_t^z\left[V_{t+1}^{n,j}\left(\mathcal{F}', z'\right) \mid \mathcal{F}, z\right] - f^{\mathcal{F}\mathcal{F}'} \\
&= \beta \mathbb{E}_t^z\left[\gamma + \pi_{t+1}^{n,j}(\mathcal{F}, z) - \vartheta \ln \varphi_{t+1}^{n,j}(\mathcal{F}' \mid \mathcal{F}, z) + \vartheta \bar{V}_{t+1}^{n,j,\mathcal{F}'}(\mathcal{F}, z) \mid \mathcal{F}, z\right] - f^{\mathcal{F}\mathcal{F}'} \\
&= \beta \pi_t^{n,j}(\mathcal{F}, z) - \beta\vartheta \mathbb{E}_t^z\left[\ln \varphi_t^{n,j}(\mathcal{F}' \mid \mathcal{F}, z) \mid \mathcal{F}, z\right] + \beta\vartheta \mathbb{E}_t^z\left[\bar{V}_t^{n,j,\mathcal{F}'}(\mathcal{F}, z) \mid \mathcal{F}, z\right] - f^{\mathcal{F}\mathcal{F}'}
\end{aligned}
$$

where the second to last line leverages the fact that firms do not forecast future input prices. There are a few things to note about this equation. First, everything except choice-specific value functions and fixed cost parameters can be observed. Using the law of large numbers, one can get an estimate of $\mathbb{E}_t^z\left[\ln \varphi_t^{n,j}(\mathcal{F}' \mid \mathcal{F}, z) \mid \mathcal{F}, z\right]$ by averaging choice-specific

probabilities for all firms that start with $\mathcal{F}$. Finally, for any initial guess of fixed costs, one can discretize expected choice-specific value functions by discretizing the AR(1) productivity process, and solving for choice-specific value functions $\left\{\bar{V}_t^{n,j,\mathcal{F}'}(\mathcal{F}, z)\right\}$in a large system of equations using the Hotz and Miller inversion.

9 Counterfactual analysis

With the model and parameter estimates above, we study the following counterfactual analyses: (1) no environmental regulations, (2) uniform environmental regulations, and (3) harmonized regulations across regions or asymmetric adoption of regulations. We will see how each scenario affects the aggregate and spatial distribution of emissions and output in the industry.

10 Conclusion

References

Aghion, Philippe et al. (2016). "Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry." In: *Journal of Political Economy* 124.1, pp. 1–51.

Ahmadi, Younes and Akio Yamazaki (2020). "The Effectiveness of Revenue-Neutral Carbon Taxes."

Alpino, Matteo, Luca Citino, and Annalisa Frigo (June 2023). *The effects of the 2021 energy crisis on medium-sized and large industrial firms: evidence from Italy*. Questioni di Economia e Finanza (Occasional Papers) 776. Bank of Italy, Economic Research and International Relations Area. URL: https://ideas.repec.org/p/bdi/opques/qef_776_23.html.

Andersson, Julius J. (2019). "Carbon Taxes and CO2 Emissions: Sweden as a Case Study." In: *American Economic Journal: Economic Policy* 11.4, pp. 1–30. ISSN: 1945-7731. DOI: 10.1257/pol.20170144.

Arkolakis, Costas and Conor Walsh (2023). *Clean Growth*. Tech. rep. National Bureau of Economic Research.

Caliendo, Lorenzo and Fernando Parro (2015). "Estimates of the Trade and Welfare Effects of NAFTA." In: *The Review of Economic Studies* 82.1, pp. 1–44.

— (2020). "The Quantitative Effects of Trade Policy on Industrial and Labor Location." In.

Chen, Qiaoyi et al. (2021). "Regulating Conglomerates in China: Evidence from an Energy Conservation Program." In: *National Bureau of Economic Research* Working paper 29066.

Christensen, Peter, Paul Francisco, and Erica Myers (2022). "Can Incentive-Based Pay Increase the Marginal Value of Public Spending on Energy Efficiency ? Experimental Evidence from the Weatherization Assistance Program."

Conte, Bruno et al. (Sept. 2021). "Local sectoral specialization in a warming world." In: *Journal of Economic Geography* 21.4, pp. 493–530. ISSN: 1468-2702. DOI: 10.1093/jeg/lbab008. eprint: https://academic.oup.com/joeg/article-pdf/21/4/493/40534183/lbab008.pdf. URL: https://doi.org/10.1093/jeg/lbab008.

Copeland, Brian R and M Scott Taylor (2004). "Trade , Growth , and the Environment." In: *Journal of Economic Literature* 42.1, pp. 7–71.

Cruz, Jose-Luis (2024). "Global Warming and Labor Market Reallocation." In: *Available at SSRN 4946752*.

Cruz, José-Luis and Esteban Rossi-Hansberg (2022). "Local Carbon Policy." In: *National Bureau of Economic Research* Working Paper 30027.

Cruz, José-Luis and Esteban Rossi-Hansberg (2024). "The economic geography of global warming." In: *Review of Economic Studies* 91.2, pp. 899–939.

Desmet, Klaus and Esteban Rossi-Hansberg (2015). "On the spatial economic impact of global warming." In: *Journal of Urban Economics* 88, pp. 16–37. ISSN: 0094-1190. DOI: https://doi.org/10.1016/j.jue.2015.04.004. URL: https://www.sciencedirect.com/science/article/pii/S0094119015000339.

— (Mar. 2024). *Climate Change Economics over Time and Space*. Working Paper 32197. National Bureau of Economic Research. DOI: 10.3386/w32197. URL: http://www.nber.org/papers/w32197.

Doraszelski, Ulrich and Jordi Jaumandreu (2013). "R and D and productivity: Estimating endogenous productivity." In: *Review of Economic Studies* 80.4, pp. 1338–1383. ISSN: 00346527. DOI: 10.1093/restud/rdt011.

Fan, Jingting, Eunhee Lee, and Valerie Smeets (2022). "High-Skill Immigration, Offshore R&D, and Firm Dynamics." In: *CEPR Discussion Paper* DP16870.

Farrokhi, Farid and Ahmad Lashkaripour (2022). "Can Trade Policy Mitigate Climate Change?" In: *STEG Working Paper Series* 034.

Gandhi, Amit, Salvador Navarro, and David A. Rivers (2020). "On the identification of gross output production functions." In: *Journal of Political Economy* 128.8, pp. 2973–3016. ISSN: 1537534X. DOI: 10.1086/707736.

Golosov, Mikhail et al. (2014). "Optimal Taxes on Fossil Fuel in General Equilibrium." In: *Econometrica* 82.1, pp. 41–88. ISSN: 0012-9682. DOI: 10.3982/ecta10217.

Greenstone, Michael et al. (2025). "Can Pollution Markets Work in Developing Countries? Experimental Evidence from India." In: *Quarterly Journal of Economics* Forthcoming.

Grieco, Paul L.E., Shengyu Li, and Hongsong Zhang (2016). "Production function estimation with unobserved input price dispersion." In: *International Economic Review* 57.2, pp. 665–690. ISSN: 14682354. DOI: 10.1111/iere.12172.

Hawkins-Pierot, Jonathan T. and Katherine R. H. Wagner (2022). "Technology Lock-In and Optimal Carbon Pricing." DOI: 10.2139/ssrn.4120154.

Hotz, V. Joseph and Robert A. Miller (July 1993). "Conditional Choice Probabilities and the Estimation of Dynamic Models." In: *The Review of Economic Studies* 60.3, pp. 497–529. ISSN: 0034-6527. DOI: 10.2307/2298122. eprint: https://academic.oup.com/restud/article-pdf/60/3/497/4468696/60-3-497.pdf. URL: https://doi.org/10.2307/2298122.

Kim, Cheolhwan (Forthcoming). "The Spatial Expansion of Environmental Policies." In.

Kleinman, Benny, Ernest Liu, and Stephen J Redding (2023). "Dynamic spatial general equilibrium." In: *Econometrica* 91.2, pp. 385–424.

Kortum, Samuel S. and David A. Weisbach (2021). "Optimal Unilateral Carbon Policy." In: *Coase-Sandor Working Paper Series in Law and Economics* 943.

Krusell, Per and Jr. Smith Anthony A (Aug. 2022). *Climate Change Around the World*. Working Paper 30338. National Bureau of Economic Research. DOI: 10.3386/w30338. URL: http://www.nber.org/papers/w30338.

Liu, Jin (2024). "Multinational Production and Innovation in Tandem." In: *Center of Economic Studies (CES) Working Paper Series* CES-24-64.

Lyubich, Eva, Joseph Shapiro, and Reed Walker (2018). "Regulating Mismeasured Pollution: Implications of Firm Heterogeneity for Environmental Policy." In: *AEA Papers and Proceedings* 108, pp. 136–142.

Melitz, Marc J (Nov. 2003). "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity." In: *Econometrica* 71.6, pp. 1695–1725. ISSN: 0012-9682. DOI: 10.1111/1468-0262.00467. URL: https://doi.org/10.1111/1468-0262.00467.

Murray Leclair, Emmanuel (2024). "Balancing Production and Carbon Emissions with Fuel Substitution." In: *Available at SSRN 4855214*.

Oberfield, Ezra and Devesh Raval (2021). "Micro Data and Macro Technology." In: *Econometrica* 89.2, pp. 703–732.

Rust, John (1987). "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher." In: *Econometrica* 55.5, pp. 999–1033. ISSN: 00129682, 14680262. URL: http://www.jstor.org/stable/1911259 (visited on 01/30/2025).

Shapiro, Joseph S. and Reed Walker (2018). "Why is pollution from us manufacturing declining? the roles of environmental regulation, productivity, and trade." In: *American Economic Review* 108.12, pp. 3814–3854. ISSN: 19447981. DOI: 10.1257/aer.20151272.

Tanaka, Shinsuke, Kensuke Teshima, and Eric Verhoogen (2022). "North-South Displacement Effects of Environmental Regulation: The Case of Battery Recycling." In: *American Economic Review: Insight* 4.3, pp. 271–88.

Weisbach, David A. et al. (2023). "Trade, Leakage, and the Design of a Carbon Tax." In: *Environmental and Energy Policy and the Economy* 4, pp. 43–90. DOI: 10.1086/722673. eprint: https://doi.org/10.1086/722673. URL: https://doi.org/10.1086/722673.

Xiang, Wei (2023). "Clean Growth and Environmental Policies in the Global Economy." In: *Available at SSRN 4619717*.

Yang, Lin et al. (2024). "Achieving Air Pollution Control Targets with Technology-Aided Monitoring: Better Enforcement or Localized Efforts?" In: *American Economic Journal: Economic Policy* 16.4, pp. 280–315.