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Abstract

We construct a spatial equilibrium model with endogenous air pollution as a by-product of production and consumption, where spatially mobile skilled and unskilled workers are affected negatively but heterogeneously by air pollution. Using a calibrated version of the model based on data for China in 2010, we show that strict regulation can be a *centripetal* force that attracts workers and production toward the regulated place, while reducing the local and overall emission of pollutants. This result is in contrast to the insights of traditional theories that see environmental regulation as a *centrifugal* force for the local economy. The migration of workers who care environmental quality, input-output linkages in domestic trade networks, and openness to international trade, work in the mechanism delivering this result. We then consider a hypothetical policy to reduce national industrial emission by 10 percent and compare strategies on how to allocate reduction responsibilities across cities. We find that concentrating responsibility in a limited number of rich cities may outperform a more equal allocation in terms of welfare and economic output.

Keywords: China, Air Pollution, Domestic migration, Spatial equilibrium model, Environmental regulation

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1 Introduction

Air pollution is one of the leading causes of death and health problems in the current world.[1] Low and middle-income countries are substantially more polluted than richer countries, and the mortality due to air pollution concentrates in those countries. China is one of the most severely affected countries by air pollution along with India. For example, it accounts for 25-30 percent of global mortality from air pollution in 2015 (Landrigan et al. 2017). Thus, as when Chinese Premier Li Keqiang declared "war against pollution" in his 2014 statement, the leaders of the Chinese government also prioritize this issue.

In principle, air pollution is a negative externality, and internalizing it through regulation is welfare-enhancing. At the same time, environmental regulation is traditionally viewed as a cost to the local economy and it works as a *centrifugal* force to drive industries out from the regulated regions. However, these mechanisms may not necessarily be simple in an economy with many interconnected regions. China is a large country with a great regional diversity, where workers and firms move across regions. Also, regions in China are tied via input-output linkages and a local shock may propagate to other regions. Since environmental regulations affect local factor prices as well as amenities, the effect of regulation does not rest only within the regulated place: it may change the prices, industrial composition, and factor allocations of other regions. Therefore, the net impact of environmental regulation on the local and nationwide outcomes will depend on many things, and are not readily obvious.

To understand the impact of environmental regulation in this complex spatial context, this paper proposes a spatial general equilibrium framework in which air pollution is endogenous as a by-product of production and consumption. By incorporating a standard trade economy model plus pollution by Copeland and Taylor (2004) and spatial equilibrium models similar to those of (Redding and Rossi-Hansberg 2017; Caliendo et al. 2018; Faber and Gaubert 2019), our model allows analysis of how a local or aggregate shock from pollution control regulations spatially propagates through trade and migration linkages. Using the model with an arbitrary number of

1. See `https://www.who.int/airpollution/en/`.

cities that is calibrated to the data of China as of 2010, we conduct various policy simulations to understand the potential effects of local and national environmental policy at aggregated and disaggregated levels.

The key contribution of this paper is that we demonstrate that the mobility of heterogeneous workers matters in determining the aggregate and distributional impact of environmental policies. Departing from the conventional theories in the literature of environment and trade, we introduce mobile workers who have heterogeneous tastes with regard to environmental quality. Thanks to this extension, we obtain several results that may contradict to traditional and popular views on how local environmental policy affect the regional economy and environment. For example, we find that there are cases where stricter environmental policies may be beneficial not only for the local air quality but also for the local economy. In addition, we also show that the same environmental policy can have different nationwide implications depending on the place where such policy is implemented. In some cases, spatially uneven policies may have greater welfare benefit than a uniform policies if we take the people's responses through migration into account.

The model has three production sectors, namely, agriculture, manufacturing, and services. Among these, we regard the manufacturing sector as the polluting sector, respecting the fact that the majority of the anthropogenically contributed air pollution comes from manufacturing emissions in China. To represent the complex mixture of regulatory tools used in local environmental control, we introduce a Pigouvian emission tax for industrial emissions that is set by local government to regulate local firms' emissions of air pollutants. This setting of endogenous pollution from the production side echoes the standard analytical framework that decomposes local emissions of pollutants into the scale (size) of the local economy, the composition of local industries, and the environmental technology of local producers (Grossman and Krueger 1995; Copeland and Taylor 2004). Quite intuitively, the model has the feature that the local emission increases with any increase in the size of the local economy, the rise of manufacturing sector's share in the economy, and the lower that environmental technology is (i.e. more emissions from a unit of manufacturing value of production).

In contrast to traditional analyses on the spatial distribution of air pollution in an international economy context (e.g. Copeland and Taylor 1994; Hubbard 2014), our model of the domestic spatial economy allows for the migration of workers across cities in China. Workers choose cities in which their welfare is maximised, and thus the expected welfare for each type is equalised in the equilibrium, following the tradition of Rosen (1979) and Roback (1982). Workers include air pollution as an local amenity in their welfare evaluation. A growing literature that reveals the demand from Chinese citizens for better ambient quality motivates us to explicitly introduce air pollution in our welfare specification. For example, studies on the hedonic pricing of housing show that people value air quality in their choice of housing location (Zheng, Fu, and Liu 2009; Zheng, Kahn, and Liu 2010; Zheng, Cao, and Kahn 2011; Zheng and Kahn 2013). Ito and Zhang (2016) use indoor air purifier purchase data between 2006 to 2012 to estimate the revealed willingness to pay (WTP) for reductions in exposure to air pollution as measured by PM_10.[2] Freeman et al. (2017) use exogenous variations in $PM_{2.5}$ generated by the power plants in distant places in a city's upwind direction and find that people are willing to give up substantial amounts of money to breathe clean air.[3] Chen, Oliva, and Zhang (2017) quantify the impact of air pollution on domestic migration in China, using the strength of thermal inversion as the exogenous source of variations in local air pollution. Their data also show that migrants head to cities with better air quality, holding other factors associated with the city's attractiveness constant.[4]

Furthermore, our model is novel because it introduces heterogeneous workers, divided into skilled and unskilled, and face different factor demands by firms. Their preferences also differ in terms of tastes on environmental quality, therefore, the skilled and unskilled are harmed differently by air pollution. The recent empirical literature reveals that skilled and unskilled workers have different tastes for amenity and this difference matters in determining which city

2. Their preferred estimates of the WTP to reduce PM10 by one unit for five years range from USD4.40 to USD5.46 per household (in 2005 exchange rate).

3. According to their main estimates, a one-unit decline in $PM_2.5$ in 2005 was worth USD 8.3 billion for the whole of China.

4. Thermal inversion is a meteorological phenomenon that reverses the normal relationship between altitude and air temperature. When it happens, air temperature in the upper-altitude is higher than that at the lower-altitudes. This is known as a typical climatic cause that worsens air pollution and they use the thermal inversion defined as above as an instrumental variable for the local level of air pollution.

they choose to live, through the balancing of their income and the cost of accessing preferred local amenities (i.e. housing cost). Moretti (2013), for example, finds that skilled labor in the U.S. will pay higher living costs than the unskilled to live in cities with superior amenity. In the context of urban air pollution in China, Chen, Oliva, and Zhang (2017) find that skilled labor more elastically responds to the level of air pollution. According to their estimates, the magnitude of the effect of a 1 $\mu g/m^3$ increase in $PM_{2.5}$ in the air on the net-migration ratio (in percent) for college graduates or above is 0.9314 while it is 0.4723 for junior-high graduates or below.

Thanks to these extensions introduced in our model, we obtain interesting insights on the spatial impacts of local environmental policy that are different from the conventional views. The conventional view on the spatial impact of environmental regulation is the *pollution haven effect* (PHE) (Copeland and Taylor 2004), which asserts that strengthening local regulations will relocate polluting industries from the regulated region to other regions with laxer policies. This intuitively straightforward prediction is doubly undesirable for policy makers because stronger regulation hurts the local economic output, and because the effectiveness of regulation in reducing pollution is somewhat offset by increased emissions outside of the regulated region. We examine how this PHE emerges in our model, and find that a stronger local regulation does not always result in a pollution haven. While a unilateral increase in emission tax in a city definitely raises the production costs there that reduces the competitiveness of local industry, however, the improved air quality in the city as well as the substitution effects among factors may however result in a relocation of workers towards the city with stricter regulations. This enhances the services sector production in the city and raises its real GDP. Moreover, the PHE outside of the city is substantially weakened.

Another feature that is important in the model is its flexible treatment of openness to international trade. Trade openness has important implications for how local regulations affect the spatial distribution of pollution within a country. Specifically, eliminating international trade tends to exaggerate PHE in the domestic economy, suggesting the importance of including the foreign market even in the case where the main focus of analysis is the distribution within a country. With international trade, the increased production cost from tougher regulation in a city results in an increase in the import of polluting varieties from foreign countries, which in turn suppresses the positive demand effect for polluting varieties from domestic suppliers. In other words, the PHE that takes place in the international arena weakens the PHE within a domestic economy. In short, more international openness is associated with a less pronounced PHE in the domestic sphere.

We then apply the model to a few policy analyses relevant to the real situation in China. Every five years, China sets a national reduction target for the aggregate industrial emission of pollutants as one of the policy targets in the Five-Year-Plan (FYP). This target is decomposed into sub-national reduction responsibilities that Provinces and prefecture-level cities try to achieve. In reality, the central government of China assigns different magnitudes of reduction responsibility (0-30 percent) across regions and cities to achieve the national target (10 percent, in 2010) as a sum of these regional reduction efforts. Reflecting this fact, we compare different spatial allocation strategies of reduction responsibility that achieve the same 10 percent national level reduction. Overall, our simulation suggests that a 10 percent reduction of aggregate emissions is likely improve the welfare of both skilled and unskilled labor. Compared to the reference strategy that assigns a uniform reduction magnitude to all, some strategies with uneven allocations are found to be more welfare-enhancing.

In addition, we find that the national 10 percent reduction policy may have a different effect on skilled workers and unskilled workers. On average, skilled workers receive a negative impact on their real income while unskilled workers enjoy economic gains, across all the allocation strategies compared. For most of the strategies, negative impacts on average real GDP are achieved by this national reduction policy, but their magnitude is tiny. There is only a 0 to -0.2 percent change of aggregate real GDP required to achieve a 10 percent reduction in aggregate industrial emissions. Surprisingly, a particular strategy that concentrates reduction responsibility in a limited number of richer coastal cities exhibits a positive return to aggregate real GDP, meaning that economically costly regulation can generate economic benefits through the reallocation of resources across space. We repeat the same exercises assuming an autarkic China where no international trade takes place. The results show that in the absence of international trade, the welfare effect for skilled worker is larger while that for unskilled workers is lower compared to the case with international trade.

While some of our results observe positive economic returns as a result of stricter regulations, our model rules out any direct mechanisms that bring economic benefit from the regulations suggested by some literature. For example, Porter and Linde (1995) argue that strict environmental regulation may induce industrial firms to invest in cleaner technology that is more productive. As a result, the implementation of regulation boosts aggregate productivity. In addition, the emerging empirical literature provides rich evidence about the direct effect of air pollution on worker productivity. As one of the latest examples from China, He, Liu, and Salvo (2019) exploit exogenous variations in exposure to $PM_{2.5}$ to find its negative impact on the productivity of industrial workers in Chinese towns.[5] However, our approach intentionally excludes the direct productivity effects of regulation and discusses the impact of regulations purely from the cost point of view for each individual firm, so that we could focus on the implications of spatial reallocation in determining the economic and welfare outcomes of environmental regulation.

Our framework contributes to the literature of economic geography from a number of perspectives. To the best of our knowledge, this paper is the first to incorporate local air pollution and a heterogeneous labor force into a quantitative spatial equilibrium model. Desmet and Rossi-hansberg (2015) are predecessors who incorporate the environmental issue into spatial general equilibrium framework, but they focus on global warming where the impact of emissions works globally, without taking into account workers' heterogeneity. Balboni (2016) studies the spatial distribution of economic activity affected by road infrastructure and localized impact of environment (sea level rise on the Vietnamese coast due to global warming), however the environment (global warming) is exogenous in her setting. Our approach is novel in that it deals with

5. See Zivin and Neidell (2018) for a short summary of global evidence in this regard.

endogenous environmental externalities in a spatial equilibrium framework where heterogeneous workers can migrate across regions and sectors.

The rest of the paper is organized as follows. Section 2 introduces the theoretical model and Section 3 summarizes the data and calibration procedures. We explain the model properties using numerical simulations of unilateral pollution control policy in Section 4. Section 5 describes how the model evaluate nationwide reduction target policies and compares different strategies of spatial responsibility allocation. Finally, Section 6 concludes the paper.

2 The Model

Our purpose is to build a quantitative model of the Chinese economy with endogenous air pollution. As motivated in the previous section, our interest rests in the spatial difference of economic activity and air pollution within China. Therefore, the model accommodates a total of N locations, consisting of $N-1$ locations in China and a single consolidated external location, the rest of the world (RoW). Locations in China, called "cities" in the rest of the paper, are denoted with index n (or i) $\in \mathcal{C}$. For the set of all locations in the model, including the RoW $\mathcal{W}$ is used for the notation.

Preference To understand the heterogeneous impact of environmental policy across different type of people, we assume that the economy is populated with two types of labor, skilled and unskilled workers. We take this dichotomous setting for workers' heterogeneity for the benefit of analytical tractability and calibration of the model to the data. Specifically, since the skill variable in our data is educational attainment, discrete categorization of the skill levels fits well in this context.

The number of skilled workers in n is denoted by L_n^k. The unskilled counterpart in n is L_n^u. The total supply of workers of type $t \in \{k, u\}$ is fixed, denoted by $L_{\mathcal{C}}^t \equiv \sum_{n \in \mathcal{C}} L_n^t$. A worker ι

of type $t \in \{k, u\}$'s preference

$$U_n^t(\iota) = \varepsilon_n^t(\iota) a_t(D_n) C_n^t B_n^t \tag{1}$$

where:

$$a_t(D_n) = \exp(-\xi^t D_n) \tag{2}$$

captures utility loss from ambient pollution in n, $D_n > 0$. We assume that a skilled worker is more sensitive to pollution, $\xi^k > \xi^u$, consistent with empirical findings such as Chen, Oliva, and Zhang (2017). $\varepsilon_n^t(\iota)$ is a Fréchet distributed idiosyncratic preference for city n by a type t worker ι, defined over all $n \in C$ for each individual worker. The distribution function is identical for all locations, with mean 1 and dispersion parameter η^t. B_n^t is the average valuation of location n's exogenous amenity other than air pollution by type t workers.

Workers consume housing C_H, traded agricultural goods C_F, traded manufacturing goods C_M, and non-traded services C_S. C_H is supplied and consumed only within the same n. For simplicity, C_H is the land whose supply is a fixed local endowment. The preference over goods is assumed to be;

$$C_n^t = \left(\frac{1}{\alpha} \left[\sum_{j=F,M,S} (C_{j,n}^t)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \right)^{\alpha} \left(\frac{C_{H,n}^t}{1-\alpha} \right)^{1-\alpha} \tag{3}$$

where $\rho > 1$ and $\alpha \in (0, 1)$. Workers of both types spend a constant fraction α of their income on goods and services other than housing. The expenditure shares within the non-housing goods are not constant and depend on local relative prices. Let $P_{j,n}$ denote the local prices of the $j (\in \{F, M, S\})$ sector goods in n. Then, the CES preference on manufacturing and traded services (the first parenthesis of (3)) ensures that the expenditure share on j-sector goods becomes $\alpha\chi_{j,n}$, where $\chi_{j,n} \equiv \frac{P_{j,n}^{1-\rho}}{P_{T,n}^{1-\rho}}$ and $P_{T,n} = \left(P_{F,n}^{1-\rho} + P_{M,n}^{1-\rho} + P_{S,n}^{1-\rho} \right)^{\frac{1}{1-\rho}}$. This assumption allows the expenditure share of non-traded services varies across locations.[6] Note that the

6. Note that we assume that the parameters governing the preference over goods expressed in (3) is the same between skilled and unskilled workers. This means that the consumption share of each category of goods is identical between the skilled and the unskilled in the same city n. This is for the sake of simplicity, but does not seem to affect the qualitative results of the model.

preference (1) ensures that skilled workers have a higher willingness to pay to reduce their exposure to air pollution. This is important for the analysis because we are interested in how environmental regulation works if there are heterogeneous mobile workers who differently value the environmental quality.

Production Sectors There are three production sectors in the model; (i) a competitive agricultural sector with constant returns to scale technology and zero trade cost between regions in China, (ii) a manufacturing sector under monopolistic competition with costly domestic trade and spatial heterogeneity of productivity that generates trade (a Ricardian), and (iii) a competitive services sector which only serves to the local market. In the model, the manufacturing sector emits air pollutants, while the other two sectors are assumed to be non-polluting. Traditionally, the literature on pollution and trade has widely used two-sector models such as that by Copeland and Taylor (2004) to incorporate the "composition effect" into the analysis. In two-sector models, there are a modern polluting (industrial) sector and a non-polluting sector. The polluting sector is subject to environmental regulations, and regulation may affect the industrial composition of the two sectors through changes in relative factor prices. We assume that the manufacturing sector is polluting based on the fact that it accounts for the largest share of the emission of ambient pollutants in China (Zheng and Kahn 2013). However, differently from the traditional way, we assume two distinctive non-polluting sectors, agriculture and services. In China, both agriculture and services employ non-negligible shares of the labor force and they are different in many aspects. Specifically, the agricultural sector mainly employs unskilled labor while the services sector uses skilled labor more intensively. Given this difference in skill intensiveness, a two-sector model which aggregates agriculture and services into one single "non-polluting sector" may oversimplify the reality of the Chinese economy. In addition, the three-sector setting fits well in our empirical context because the data (output and employment) we use for calibration report the numbers for these three sectors.

Agricultural Production We assume that the agricultural sector is traditional and hires only unskilled labor. For the benefit of simplicity, we further assume that the agricultural output can be traded without trade cost, so that the price can be normalized to $P_{F,n} = 1, \forall n \in \mathcal{W}$. Specifically, the production is constant returns to scale and has the following form,

$$Y_{F,n} = A_{F,n} L^u_{F,n} \tag{4}$$

where $A_{F,n}$ is local productivity shifter. Local endowments such as land area and fertility are considered to be entered in this productivity shifter. $L^u_{F,n}$ is the employment of unskilled labor in the agricultural sector in n. Let w^u_n denote the wage of the unskilled labor, then, in the equilibrium,

$$w^u_n = A_{F,n} \tag{5}$$

Production Technologies in the Manufacturing Sector The production technology of the manufacturing sector closely follows the Ricardian trade model proposed by Eaton and Kortum (2002), which have widely been used to study the domestic economic geography (see, Donaldson and Hornbeck 2016; Caliendo et al. 2018; Faber and Gaubert 2019). There are quite a few advantages of adopting their model. First, it allows dealing with an arbitrary number of locations that engage in trade. Second, while the model by Eaton and Kortum (2002) was originally designed to study international trade where the factors (such as labors) are immobile across national borders, the model can easily be extended to accommodate the migration of production factors. Third, the model can directly incorporate the canonical model of pollutant emission of Copeland and Taylor (2004).

There are infinitesimal intermediate manufacturing varieties in a fixed interval, indexed by $x \in [0, 1]$. An x-variety firm uses inputs from manufacturing and local services as well as two types of labors. A local competitive manufacturing final producer combines all the intermediate varieties that can be sourced from any cities within China and RoW and produce a manufacturing composite. This local final producer sells the composite to the local final consumers and local producers in manufacturing and services. The primary production unit in the manufacturing sector is the firms that produce manufacturing intermediates. Each of these firms produces an intermediate variety using a composite of inputs as specified below. Production by the intermediate firms generates an undesirable by-product, which is called pollutant. To reduce the emission of pollutant, the firm needs to divert a fraction of its inputs to abatement activities. Net emissions after abatement are a fraction of the primary gross emission.

Specifically, an intermediate x-variety producer in city n has the following technology.

$$\begin{cases} q_{M,n}(x) & = [1 - s_n(x)]\, \phi_n(x) A_{M,n} \tilde{m}_n(x) \\ \tilde{z}_{M,n}(x) & = \lambda_{M,n} \phi_n(x) A_{M,n} \tilde{m}_n(x) \\ z_{M,n}(x) & = [1 - s_n(x)]^{\frac{1}{\delta}}\, \tilde{z}_{M,n}(x) \end{cases} \tag{6}$$

where $q_{M,n}$ is the output volume, $\phi_n(x)$ is a variety x-specific random variable drawn from a Fréchet distribution with shape parameter $\tilde{\theta}$ and mean 1 whose CDF is given by $F(\phi) = \exp[\phi^{-\tilde{\theta}}]$. As in Eaton and Kortum (2002), $\phi_n(x)$ represents the efficiency of variety x production in city n. $A_{M,n}$ is a productivity shifter common to all manufacturing sector firms in n. This shifter is exogenous to individual manufacturing firms. $\tilde{m}_n$ is the composite of input in Cobb-Douglass form which is given by

$$\tilde{m}_n(x) = \left[l^k_{M,n}(x)\right]^{\gamma^k_M} \left[l^u_{M,n}(x)\right]^{\gamma^u_M} \left[m^M_{M,n}(x)\right]^{\gamma^M_M} \left[m^S_{M,n}(x)\right]^{\gamma^S_M} \tag{7}$$

where l^k_M, and l^u_M are skilled labor and unskilled labor inputs, respectively. $m^M_{M,n}$ is the input of manufactured intermediate goods for manufacturing production, while $m^S_{M,n}$ is the input from services sector.The technology is constant returns to scale at the firm level with the input coefficients and satisfies that $\sum_{j' \in k,u,M} \gamma^{j'}_{M,n} = 1$. $s_n \in [0, 1]$ is the share of input composite $\tilde{m}_n$ diverted for the pollution abatement activity. In other words, $(1 - s_n)$ of input is kept for the main production.

The second equation in (6) assumes a simple relationship between the inputs and generated pollution. The gross emission before abatement, $\tilde{z}_{M,n}(x)$ is assumed to be proportional to the total input ($\tilde{m}_{M,n}$) the firm uses for its operation. This is a strong but common assumption in this type of models for the benefit of analytical tractability. $\lambda_{M,n} > 0$ is coefficient that specifies the relationship between the input and emissions.

The third equation in (6) is for the end-of-pipe abatement technology. $z_{M,n}$ refers to net emissions, which is the pollution that is finally emitted to the environment after abatement. $z_{M,n}$ depends on the gross emission and the abatement effort as measured by the share of the diverted input for abatement activity (s_n). For a given level of $\tilde{z}_{M,n}$, the net emission is smaller if more resources are used for abatement (i.e. larger s_n). $\delta \in (0, 1)$ is an inverse measure of abatement efficiency. A higher δ means that end-of-pipe technology is less efficient and more final pollution is emitted for given the potential emission and abatement resources.

Intermediate firms are price takers and perfect competition works in the market. Let $w_n^t, t \in \{k, u\}$, be the wages of type t worker, $P_{M,n}$ be the price of the final manufacturing composite, and $P_{S,n}$ be the services price in n, respectively. Since the input bundle $\tilde{m}_{M,n}$ is an output of the technology in (7), the cost minimization on the choice of primary inputs yields the following unit cost for producing a bundle, which is denoted by $\tilde{c}_{M,n}$,

$$\tilde{c}_{M,n} = \Psi \left[w_n^k\right]^{\gamma_M^k} \left[w_n^u\right]^{\gamma_M^u} \left[P_{M,n}\right]^{\gamma_M^M} \left[P_{S,n}\right]^{\gamma_M^S} \tag{8}$$

where Ψ is a constant.[7] Following studies such as Antweiler, Copeland, and Taylor (2001), Copeland and Taylor (2004), and Shapiro and Walker (2018), we summarise the set of environmental regulations into a Pigouvian emission tax on unit emission of pollutant by the local manufacturing sector, denoted by ζ_n in n (the assumptions for ζ_n will be discussed below). Then, from (6) and $0 \geq s_n \geq 1$,the profit maximization problem of a firm becomes:

$$\max_{\tilde{m}_{M,n}(x), z_{M,n}(x)} p_{M,n} \left(\frac{z_{M,n}(x)}{\lambda_{M,n}}\right)^{\delta} \left(\phi_n(x) A_{M,n} \tilde{m}_{M,n}(x)\right)^{1-\delta} - \tilde{c}_{M,n}\tilde{m}_{M,n}(x) - \zeta_n z_{M,n}(x) \tag{9}$$

7. Namely, $\Psi \equiv \left[(\gamma_M^k)^{\gamma_M^k} (\gamma_M^u)^{\gamma_M^u} \prod_{j'=M,S} (\gamma_M^{j'})^{\gamma_M^{j'}}\right]^{-1}$.

The first order conditions for the problem (9) yields the optimal unit cost which is given by $\frac{c_{M,n}}{\phi_n(x)^{1-\delta}A_{M,n}^{1-\delta}}$, where

$$c_{M,n} = \left(\frac{\tilde{c}_{M,n}}{1-\delta}\right)^{1-\delta}\left(\frac{\lambda_{M,n}\zeta_n}{\delta}\right)^{\delta} \tag{10}$$

A final manufacturing good is produced by a competitive local aggregator. The final good is a composite produced by a CES function that use all the varieties $x \in [0, 1]$. Input varieties are sourced from the lowest cost region across all the locations $n = 1, ..., N$, including an iceberg trade cost to ship the good from i to n, $\tau_{ni} > 1$. The aggregation function is

$$Q_{M,n} = \left[\int q_{M,n}(x)^{\frac{\sigma_M-1}{\sigma_M}}dx\right]^{\frac{\sigma_M}{\sigma_M-1}} \tag{11}$$

where σ_M is the elasticity of substitution. The price of the input variety x used for final production in n satisfies $p_{M,n}(x) = \min_{i\in 1,...,N}\left\{\frac{c_{M,i}\tau_{ni}}{A_{M,i}^{1-\delta}\tilde{\phi}_i(x)}\right\}$. Exploiting the property of the Fréchet distribution for $\phi_i(x)$, the share of expenditure on varieties from region i in the total expenditure for manufacturing varieties in n is given by,

$$\pi_{ni}^M = \frac{(\tau_{ni}c_{M,i})^{-\theta}(A_{M,i})^{\theta}}{\sum_{i'=1}^N(\tau_{ni'}c_{M,i'})^{-\theta}(A_{M,i'})^{\theta}} \tag{12}$$

and the price of the final manufacturing good available in n is then given by

$$P_{M,n} = \left[K_M\sum_{i=1}^N(\tau_{ni}c_{M,i})^{-\theta}(A_{M,i})^{\theta}\right]^{-\frac{1}{\theta}} \tag{13}$$

where, $\theta \equiv \frac{\tilde{\theta}}{1-\delta}$ and $K_M \equiv \left(\Gamma\left(\frac{\theta-\sigma_M+1}{\theta}\right)\right)^{\frac{1}{1-\sigma_M}}$ is a constant.

Services Sector Goods Service sector goods are treated as non-traded, in a similar way to Caliendo et al. (2018) and other studies. We admit that this is a strong assumption. This is because the overall trade cost required to deliver services to a distant customer seems to be substantially higher than that of manufactured goods.[8] Therefore, in the current model, we treat them as non-traded and the services firms only serve local customers within the city n. A services sector firm combines skilled labor, unskilled labor, and manufactured goods. The production function is given by:

$$Q_{S,n} = A_{S,n}[L^k_{S,n}]^{\gamma^k_{S,n}}[L^u_{S,n}]^{\gamma^u_{S,n}}[m^M_{S,n}]^{\gamma^M_{S,n}} \tag{14}$$

where, $m^M_{S,n}$ is manufacturing inputs of the services sector.[9] The technology is constant returns to scale such that $\sum_{j'\in k,u,M}\gamma^{j'}_{S,n} = 1$ is satisfied. Note that we assume that $\gamma^{j'}_{S,n}$ varies across cities. Later we detail how we calibrate these with the data. $A_{S,n}$ is the productivity shifter of the services sector in n that is exogenous for individual services firms. Let $P_{S,n}$ denote the local price of the services goods in n. Cost minimization and free entry ensures that the price should satisfy

$$P_{S,n} = \frac{\Psi_{S,n}}{A_{S,n}}(w^k_n)^{\gamma^k_{S,n}}(w^u_n)^{\gamma^u_{S,n}}(P_{M,n})^{\gamma^M_{S,n}} \tag{15}$$

where $\Psi_{S,n}$ is a constant.[10]

Goods Market Clearing In the equilibrium, all markets clear. Let $Y_{j,i}, \forall j \in \{F, M, S\}$ denote the total value of production of sector j in i. Similarly, $E_{j,n}$ denotes the value of expenditure on sector j in n. Firstly, the total agricultural supply should be equal to the demand,

$$\sum_{i\in\mathcal{W}} Y_{F,i} = \sum_{n\in\mathcal{W}} E_{F,n} \tag{16}$$

For manufacturing varieties, the total value of production must be equal to the sum of demand from all the potential destinations, i.e., $Y_{M,i} = \sum_{n\in\mathcal{W}} E_{M,n}\pi_{ni}$. Using (12) and (13), this

8. According to the main estimates by Gervais and Jensen (2019) on U.S. data, trade costs for the eleven sub-sectors in the services category range from 3.95 times (wholesale trade) to 28.67 times (real estate and leasing).

9. The services sector of course uses agricultural goods as well as land as inputs, however, we drop these from the production function for the sake of simplicity. According to China's input-output tables, their contribution is very marginal for the services sector, the coefficients for agricultural inputs and land are 0.016 and 0.039, respectively.

10. $\Psi_{S,n} = (\gamma^k_{S,n})^{-\gamma^k_{S,n}}(\gamma^u_{S,n})^{-\gamma^u_{S,n}}(\gamma^M_{S,n})^{-\gamma^M_{S,n}}$.

condition can be rewritten as:

$$Y_{M,i} = \tilde{A}_{M,n} c_i^{-\theta} \sum_{n \in \mathcal{W}} \tau_{ni}^{-\theta} E_{M,n} P_{M,n}^{\theta} \tag{17}$$

where, $\tilde{A}_{M,n} \equiv K A_{M,n}^{\theta}$. Since the services sector goods are non-traded, the local production should match local demand. Mirroring this equality in the services sector, the sum of the production values of the two traded sector should be equal to the sum of the demand for them, in every location. Therefore, we have

$$Y_{S,n} = E_{S,n}, \quad \forall n \in \mathcal{W} \tag{18}$$

$$Y_{F,n} + Y_{M,n} = E_{F,n} + E_{M,n}, \quad \forall n \in \mathcal{W} \tag{19}$$

Industrial Emission Revenue from emission charge As a means of environmental control, local government collects emission charges from manufacturing firms. Let $Z_{M,i}$ be the aggregate amount of pollutant discharged to the environment from manufacturing firms in i. Given the unit emission charge ζ_i in i, the i's government collects $\zeta_i Z_{M,i}$. The first order condition for (9) yields:

$$\zeta_i Z_{M,i} = \delta Y_{M,i} \tag{20}$$

Local government employs skilled workers to implement pollution control. No production technology is specified for this control, while the demand for skilled workers of this environmental control task just has to satisfy a simple resource constraint,

$$w_i^k L_Z^k = \zeta_i Z_{M,i} \tag{21}$$

which means that the wage payment to the skilled employees equals to the revenue from emission charges collected from the manufacturing firms. This assumption can also be interpreted as that the local government rebates back the collected emission charges to skilled workers.

Land Market Local government collects land rent revenue and redistributes it to residents. For simplicity, we assume that the government redistributes the revenue so that it augments their wage income by the factor of $(1+\mu)$ where $\mu > 0$. From the utility function, the total expenditure on land in n is $r_n H_n = (1-\alpha)(1+\mu)(w_n^k L_n^k + w_n^u L_n^u)$. At the same time, the revenue should be equal to the total amount redistributed, which means $r_n H_n = \mu(w_n^k L_n^k + w_n^u L_n^u)$. Then, $\mu = \frac{1-\alpha}{\alpha}$. This yields the equilibrium land rent given as

$$r_n = \frac{1-\alpha}{\alpha} \frac{w_n^k L_n^k + w_n^u L_n^u}{H_n} \tag{22}$$

Expenditure on Goods As explained above, the income of a type t worker is wage income plus rebated land rent, thus w_n^t/α. Production of manufacture and services requires input goods other than labor. Given these, the expenditure for sector j in location n becomes:

$$\begin{aligned} E_{F,n} &= \chi_{F,n}(w_n^k L_n^k + w_n^u L_n^u) \\ E_{M,n} &= \chi_{M,n}(w_n^k L_n^k + w_n^u L_n^u) + (1-\delta)\gamma_M^M Y_{M,n} + \gamma_{S,n}^M Y_{S,n} \\ E_{S,n} &= \chi_{S,n}(w_n^k L_n^k + w_n^u L_n^u) + (1-\delta)\gamma_M^S Y_{M,n} \end{aligned} \tag{23}$$

Labor incomes and labor market clearing According to the assumptions about production functions, the total wage earnings of skilled and unskilled labors are given as follows,

$$\begin{aligned} w_i^k L_i^k &= \Big((1-\delta)\gamma_M^k + \delta\Big) Y_{M,i} + \gamma_{S,n}^k Y_{S,i} \\ w_i^u L_i^u &= Y_{F,i} + (1-\delta)\gamma_M^u Y_{M,i} + \gamma_{S,n}^u Y_{S,i} \end{aligned} \tag{24}$$

Note that these equations are the labor market clearing conditions, given that the total labor supply of type t workers in i is $L_i^t, t \in \{k, u\}$.

Emissions from Consumption Recent studies reveal that emissions from the consumption side, which arise when consumers use manufacturing products, are becoming increasingly important

(Liu et al. 2016; Li et al. 2017).[11] Not only in the advanced countries, even in several developing countries such as China, emissions from the use of transportation (for example, vehicles) as well as emissions from housing (cooking and heating) consists a large share in the emission inventories. Therefore, here we introduce a simple mechanism of emissions from consumption, $Z_{R,n}$ as follows. Specifically, we assume that $Z_{R,n}$ is proportional to the real manufacturing expenditure with the fixed coefficient $\lambda_{R,n}$. Assume that the use of manufactured goods generates pollution (car, cooking equipment, air conditioning and heating, processed fuels, etc.). As the total consumption expenditure on manufacturing in n is given by $\chi_{M,n}(w_n^k L_n^k + w_n^u L_n^u)$ along with the price $P_{M,n}$, the residential emissions is given by

$$Z_{R,n} = \lambda_{R,n} \frac{\chi_{M,n}(w_n^k L_n^k + w_n^u L_n^u)}{P_{M,n}} \tag{25}$$

Emission to Pollution The anthropogenic emissions of pollutants such as SO2, NOx, and the primary emission of $PM_{2.5}$, contributes to the formulation of air pollution through various complex chemical reactions. Other than those pollutants from economic activities, sources such as sand storms from deserts, volcanos, and sea salt, plays an important role in determining the area's level of pollution, with climate conditions such as wind, precipitation, humidity, and temperature. Thus, the mechanism that determines how emissions from human activity affects the local ambient quality is very complex, and a full-scale scientific weather model is needed to make a prediction of air quality for a given level of emissions. Unfortunately, the predictive models that are commonly used are designed for a short term prediction within a small geographical area. In our case, we intend to connect the annual sum of emissions to the annual average level of air quality, within a relatively large geographical unit.

11. Karagulian et al. (2015) conduct a meta-analysis of local studies across the world and find that industrial emission constitutes 16-27 percent of the PM 2.5 pollution. The residential emission contributes 15-21 percent, and traffic contributes 15-18 percent, respectively (Aunan, Hansen, and Wang 2018; Karagulian et al. 2015). Liu et al. (2016) estimate that industry contributed around 50 to 60 percent of PM 2.5 while residential emission is responsible for 30 to 40 percent of it, respectively in Beijing, Tianjin, and Hebei area, throughout 2010. Transport and power contributed relatively smaller share. These findings motivate us to include emissions from non-industrial sources that we summarize as residential emission.

Given this scientific limitation, a simple empirical relationship between local emission and local air quality is used for the mapping of emissions into pollution. Let D_n denote the level of air pollution (PM2.5 concentration) in n observed as concentration in the air (with the unit of $\mu g/cm^3$, for example), after the chemical process that transforms anthropogenic and natural primary pollutants into harmful particulates. Assume that D_n has the following relationship with the anthropogenic emissions in n; $Z_n = Z_{M,n} + Z_{R,n}$, the sum of emissions from manufacturing production and residential emissions is then:

$$D_n = f(\tilde{X}_n) Z_n^{\kappa} \tag{26}$$

where κ is a coefficient on emission and $f(\tilde{X}_n)$ is a function of other local characteristics denoted by $\tilde{X}_n$.

Pollution control policy (emission tax) Local government sets the Pigouvian tax rate, denoted as ζ_n, as an emission charge. The literature on China's local environmental regulations (Rooij and Lo 2010; Wu et al. 2013; Wang 2013; Zheng et al. 2014; Jin, Andersson, and Zhang 2016) points out that China's local leaders compete with each other in their race for promotion among the hierarchy of the Communist Party. For prefecture level leaders, getting high performance evaluations from their upper-level officials (i.e. Provincial government), is thus the priority that determines their policy implementation. In the past, local GDP was the main indicator used for evaluation. This economy-focused incentive system has long been criticized for a lack of consideration of sustainability. However, since the tenth Five Year Plan (FYP) period was initiated in 2001, the central government has begun to include environmental targets, such as emission reduction targets for air pollutants. Since the eleventh FYP (2006-2010), the Chinese government has introduced the target responsibility system (TRS) for environmental pollution that binds lower-level officers to accomplish the targets agreed with their upper-level leaders.

Our modelling of the local government problem reflects this Chinese context. In particular, we assume that the evaluation of the government n, denoted by V_n is defined by

$$V_n = -\xi_n^g Z_{M,n} + G_n^{\omega} \tag{27}$$

where $G_n = w_n^k L_n^k + w_n^u L_n^u$ is city n's total value added (GDP), and $\omega \in (0, 1)$. $\xi_n^g > 0$ is the city n specific coefficient that reflects how much upper-level governments stress environmental quality in their evaluation of the government of n. The local government choose ζ_n that maximizes V_n. It is assumed that the local government ignores (or cannot know) the impact of its ζ_n on population, L_n^k and L_n^u, and the price index $P_{T,n}$, and regards them as given.

Under this assumption, a similar derivation for the Samuelson condition as in Antweiler, Copeland, and Taylor (2001) applies. The first order condition with respect to ζ_n in (27) yields:

$$\zeta_n = \frac{\xi_n^g}{\omega} G_n^{1-\omega} \tag{28}$$

(28) tells us that the emission tax is higher where the economic scale is larger. This is quite a simple specification, however, it reflects the observed relationship between emission intensity and the city's economic scale described in Section A.3; which is that, the larger the city's economic scale is, the smaller the emission intensity from manufacturing. Given the pollution supply function (28), and the pollution function (20), the equilibrium industrial emission is:

$$Z_{M,n} = \frac{\delta\omega}{\xi_n^g} G_n^{\omega} \frac{Y_{M,n}}{G_n} \tag{29}$$

Migration It has long been argued that domestic migration, especially rural-to-urban migration, is severely restricted in China under the "hukou" system. The majority of econometric research studies on China up to the early 2000s assumed that labor is immobile due to the hukou restriction (e.g. Au and Henderson 2006b, 2006a). However, this restriction has been gradually eased during the past two decades and the Chinese labor force is currently very mobile, although there still remains substantial social and institutional discrimination against migrants(Song 2014). In terms of volume, rural to urban migration has been very large and we cannot explain the massive urbanization and industrialization of China in the past few decades without inter-prefectural and inter-provincial migration. The urbanization rate (urban population share in total population) rose from 18 percent in 1978 to 53 percent in 2011 (Chen et al. 2013). In the past 30 years, urban population has increased by 440 million, and half of that is said to be attributable to rural to urban migration. Given these facts, it has become more appropriate than ever before to treat labor as geographically mobile in China. For example, using a similar approach, Baum-Snow et al. (2015) conducted a simulation study to assess the impact of road network improvements on population and production, assuming both perfect labor mobility and immobility.We follow the widely used Fréchet distributed "mobility frictions" (Baum-Snow et al. 2018) that are also assumed in the studies such as Baum-Snow et al. (2015), Donaldson and Hornbeck (2016), Redding (2016), Balboni (2016), and Faber and Gaubert (2019). In contrast to these studies, however, we assume that both skilled and unskilled workers migrate across prefectures in China searching for the place that offer them the highest utility. For each type, the expected utility should be equalized across space in the equilibrium. Noting that the real income of type t worker living in n can be written as $\left(\frac{1}{P_{T,n}}\right)^{\alpha}\left(\frac{H_n}{G_n}\right)^{1-\alpha} w_n^t$, and that the idiosyncratic location preference ϵ is Fréchet distributed, the spatial distribution of type t workers is then given by,

$$\frac{L_n^t}{L_C^t} = \frac{\left(\tilde{B}_n^t \exp(-\xi^t D_n) \frac{H_n^{1-\alpha} w_n^t}{P_{T,n}^{\alpha} G_n^{1-\alpha}}\right)^{\eta^t}}{\sum_{n' \in C} \left(\tilde{B}_{n'}^t \exp(-\xi^t D_{n'}) \frac{H_{n'}^{1-\alpha} w_{n'}^t}{P_{T,n'}^{\alpha} G_{n'}^{1-\alpha}}\right)^{\eta^t}}, \quad \forall n \in C \tag{30}$$

For outside of China, the RoW, population is fixed.

Equilibrium The *equilibrium* of this economy can be defined as follows: *Given the parameters,* $\{\theta, \delta, \alpha, \tau_b, \eta^k, \eta^u, \xi^k, \xi^u, \rho, \omega, \kappa, \gamma_j^k, \gamma_j^u, \gamma_j^M, \gamma_j^S\}$*, inter-city trade cost matrix* $\{\tau\}$*, and exogenous variables* $\{A_{M,i}, A_{S,i}, B_i^k, B_i^u, \zeta_i^g\}$*, the equilibrium is the vectors of quantities* $\{Z_{M,i}, Z_{R,i}, D_i, L_i^k, L_i^u\}$*, prices* $\{w_i^k, w_i^u, r_i, \zeta_i, P_{M,i}, P_{S,i}\}$*, values* $\{Y_{F,i}, Y_{M,i}, Y_{S,i}, E_{F,i}, E_{M_i}, E_{S,i}\}$*,* *and the manufacturing trade share matrix $\{\pi_{ni}\}$, that are given as the solutions to (26), (20), (25), (30), (24), (22), (28), (13), (15), (18), (19), (23), and (12).*

3 Quantification of the Model

Since the model cannot be solved analytically, we calibrate it to the observed situation of China in 2010 to conduct numerical exercises. The data for the observed variables include the population of skilled and unskilled workers, the value added of three industrial sectors (primary, secondary, and tertiary), the $PM_{2.5}$ concentration, the emission of pollutants, and other variables that are used in the estimation procedure for some of the model parameters. The details of the data and the calibration strategy are explained in Section A.2 and Section A.4.

We combine multiple data sources to conduct the analysis. We focus on the 296 geographical units (270 prefecture-level cities and 26 counties directly under the Provinces) in the Eastern half of the mainland China. Four provinces and autonomous regions, namely, Inner Mongolia, Xinjiang, Qinghai, Tibet, and islands (such as Hainan Province) are not included in these 296 units and treated as the RoW. Economic variables, such as the value added and employment of industries, are taken from the *China City Statistical Yearbook*, *China Region Economy Statistical Yearbook*, as well as the online supplementary material of Baum-Snow et al. (2017). Our analysis needs the amount of skilled and unskilled worker in each city. The best available proxy for the people's skill level is educational attainment of the residents. Since the data on educational attainment of workers are not available (only adult population by degrees is available), we assume that the share of the skilled worker in all the worker in a city is equal to the share of adult population with at least senior high school degree out of the total adult population in the city. Environmental variables such as $PM_{2.5}$ concentration and emissions of air pollutants are from the sources using satellite images provided by Donkelaar et al. (2016) and the MEIC database.[12]

The model requires the estimate of the iceberg trade cost for manufacturing intermediates

12. `http://www.meicmodel.org/index.html`

between each pair of cities and between the RoW, τ_{ni}. Since the model yields a gravity equation of trade flow between each pair of cities, we can recover τ_{ni} as Caliendo et al. (2018) if we have a bilateral trade flow statistics. However, there is no available data on the bilateral flow of trade among the pairs of prefecture-level cities in China. Therefore, we have to construct it based on the distance and the quality of transport infrastructure. Specifically, we closely follow the data and the method by Baum-Snow et al. (2018) that uses the digitized map of China's road network as of 2010 which is provided in their on-line appendix and calculate the shortest paths (shortest travel time) between each pair of cities by the Dijkstra algorithm (the average travel speed according to the grade of motorways is reflected). Then, we convert the calculated travel times in hours between each pair of cities into a matrix of iceberg trade cost.[13]

There is no information available for the wage rates of skilled workers and unskilled workers at the level of prefecture cities. We impute the skill-based local wages exploiting the model's equilibrium conditions and the sector-specific wage rates from the national level provided in the *China Statistical Yearbook*. Through the process of recovering the local wages for the skilled and unskilled workers, we also derive sector-specific input parameters for skilled and unskilled, γ_j^k and γ_j^u, so that the model based national average wage rates become equal to the observed ones.

We estimate the remaining parameters; goods expenditure share α, international border effect τ_b, labor supply elasticity η^t and taste for air pollution ξ^t for each of $t \in k, u$, the elasticity of substitution among three category of goods ρ, the emission tax elasticity to GDP, ω, and the elasticity of city $PM_{2.5}$ with respect to city's pollutant emissions κ. Among them, the most important parameters are η^t and ξ^t, which are found to substantially affect the simulation results. To estimate these parameters, we exploit the equilibrium conditions that pin down the labor incomes (24) and migration (30). From (24) and (30), the population of type t labor in n can be

13. Specifically, the trade cost between city i and j, τ_{ij}, is given by $\tau_{ij} = 1 + 0.004(\text{hours of travel time}_{ij})^{0.8}$. See Baum-Snow et al. (2018) for the detail.

expressed as:

$$\ln L_n^t = \beta_0 - \xi^t \frac{\eta^t}{\eta^t + 1} D_n + \frac{\eta^t}{\eta^t + 1} \ln \widetilde{W_n^t} + \tilde{\epsilon^t}_n, \quad \forall n \in C \tag{31}$$

where: $\widetilde{W_n^k} \equiv \frac{\left((1-\delta)\gamma_M^k+\delta\right)Y_{M,n}+\gamma_{S,n}^k Y_{S,n}}{P_{T,n}^{\alpha} G_n^{1-\alpha}}$, $\widetilde{W_n^u} \equiv \frac{Y_{F,n}+(1-\delta)\gamma_M^u Y_{M,n}+\gamma_{S,n}^u Y_{S,n}}{P_{T,n}^{\alpha} G_n^{1-\alpha}}$, and D_n is the level of pollution derived by using the annual average concentration of $PM_{2.5}$ as a proxy, respectively. The equation (31) gives the relationship between the population of type t worker in n and the air pollution and the real wage in n. We estimate (31) to obtain the values for ξ^t and η^t.

This method, of course, could be prone to endogeneity issues. Specifically, the OLS estimate of ξ^t can be overestimated (in terms of magnitude) if an unobserved productivity of the services sector raises both the services sector share in the city as well as the labor supply to the city. Similarly, the OLS estimates of η^t tend to be underestimated by the existence of unobserved amenities that attract workers. On the other hand, unobserved productivity shocks may cause an overestimation of η^t. We borrow from existing studies to address these identification concerns. For air pollution terms that are critical in estimating ξ^t, we follow Freeman et al. (2017) and instrument air pollution (measured by $PM_{2.5}$ concentration) by the SO_2 emission from thermal power plants within the up wind direction from the city (excluding that from their own city). The identification assumption is that the thermal plant emission from upwind locations affect the city's worker population only through its impact on air pollution conditional on the control variables. For the estimation of η^t, we benefit from Baum-Snow et al. (2018) who estimated the impact of road infrastructure in 2010 on the employment and economic outcomes of Chinese cities. They instrument 2010 infrastructure variables with 1962 infrastructure variables. For identification, we assume that the 1962 infrastructure affects the population of 2010 skilled (unskilled) workers only through the real wage paid to them conditional on the controls.

Through these estimations, we try to verify that the model's equilibrium condition holds in the real world in a meaningful way. Our estimates of labor supply elasticities, η^t, welfare effects of air pollution, ξ^t, and the Pigouvian tax parameter, ω, are within reasonable ranges compared to the existing studies, and are consistent with the model's assumptions. The details

Table 1: Parameter Values

Parameter	Value	Source
θ	5	Baum-Snow et al. (2018)
δ	0.011	Shapiro and Walker (2018)
α	0.87	Estimated (expenditure share on housing, based on *China Statistical Yearbook 2011*)
τ_b	1.68	Estimated (applying equation (53) in the Appendix to China's export and import)
η^k	3.52	Estimated (equation (31))
η^u	1.16	Estimated (equation (31))
ξ^k	0.013	Estimated (equation (31))
ξ^u	0.0095	Estimated (equation (31))
ρ	3.45	Estimated (Search the value that minimize observed and model expenditure share over three goods category, at the Provincial level))
ω	0.466	Estimated (equation (58) in the Appendix)
κ	0.16	Estimated (OLS regressing $PM_{2.5}$ on industry and consumption emissions)

Source: Author

of the calibration and estimation is explained in Section A.4. Of course, it should be noted that our verification through estimation addresses a subset of equilibrium conditions. It is desirable therefore to have a more comprehensive check on whether the model well replicates the observed endogenous variables, as Tombe and Zhu (2019) do by exploiting intertemporal changes in the exogenous variables. Unfortunately, however, the full set of data required for that analysis is available only for 2010, preventing such an exercise that requires a city-level panel dataset. Minding these limitations, we examine how the qualitative results of the simulation change by the choice of these parameters in Section 5.

We calibrate the following the remaining parameters borrowing the knowledge from existing literature: the Fréchet dispersion parameter for manufacturing productivity, θ, and the input share of pollutant emission (equivalent to the inverse of abatement efficiency), δ. Table 1 summarizes the calibrated and estimated parameters used in the simulation exercises.

4 Simulation Exercises to Study the Model's Properties

The main purpose of this paper is to understand the impact of pollution control policy on environmental, economic, and welfare outcomes. In what follows, we study several theoretical implications of the model using the calibrated model. We specifically focus on the exogenous change to pollution control policy which is captured by $\widehat{\xi_n^g}$. This parameter represents how much the evaluation of local government n is damaged by an increase in industrial emissions from its jurisdiction. We first examine how a regulatory shock to a particular city n, captured by $\widehat{\xi_n^g}$, will have spatial impacts on economic and environmental variables. An increase in ξ_n^g for city n affects the outcomes of itself. In addition, it also have varied impacts on other cities. The signs and the magnitudes of the own effect and the spillover effects are not readily obvious, as the model accommodates various channels of impact that mutually interfere with each other.

Given this analysis, we further seek for desirable spatial allocation of responsibility to reduce emissions. Setting an aggregate emission reduction target to 10 percent, we compare various weighting strategies that differentiate localized reduction responsibility across cities, in addition to a uniform allocation that assigns the same magnitude (in percent) of reduction responsibility to all cities. We find that some strategies are superior to the uniform strategy. Interestingly, even though the stronger pollution control is costly for individual firms and we rule out technological mechanisms that cause that stricter regulation raises productivity, we find that a few strategies may result in an increase in national real GDP. We discuss in detail how these strategies are different in terms of environmental, economic and welfare outcomes.

Throughout the analysis, we examine how the key assumptions of the model affect the derived elasticities with respect to the shocks in the exogenous variables. Specifically, we compare our baseline model with counterfactual models that shut-out three important ingredients; the migration of workers, international trade, and preference for air quality. The counterfactual models give significantly different outcomes from those of the baseline, meaning that the relevance of these key assumptions as well as the potential sensitivity to the estimated parameter values.

As shown in the Appendix A.1, the model allows us to employ the "method of change" proposed by Dekle, Eaton, and Kortum (2008) to solve for the counterfactual equilibrium without knowing the levels of unobserved variables.

4.1 Impact of Unilateral Policy Change in a City

We first illustrate the spatial propagation of impact from a unilateral policy change in a single city. As an example, we choose Beijing, Wuhan, and Deyang, and examine how the impact differs depending on the place the policy shock originates from. Let $i' \in \{\text{Beijing, Wuhan, Deyang}\}$ denote the city that receives unilateral policy change. We compute the elasticity of outcome variables in all the 296 cities with respect to $\widehat{\boldsymbol{\xi}^g}$, which is a vector whose i'-th element is $\widehat{\xi^g_{i'}} = 1.1$ while keeping other elements to $\widehat{\xi^g_i} = 1 \quad \text{for } i \neq i'$. This means that the city i' increases its regulatory parameter by 10 percent, while other cities keep it unchanged. The choice of magnitude at 10 percent is reasonable considering the policy context of China around 2010. China has set national level environmental targets for every Five-Year Plan (FYP), since its 11th FYP for the years 2006-2010. Under this FYP, a nationwide reduction target of the emission of industrial SO_2 was set to 10 percent of the level in 2005. In the 12th FYP, the SO_2 reduction target was set to 8 percent of the 2010 emission level, while the target of 10 percent reduction for NO_x was added(Aunan, Hansen, and Wang 2018).[14] As (29) implies, if G and Y_M are constant, the elasticity of $Z_{M,n}$ with respect to ξ^g_n is -1. Therefore, a naive policy response to the national target to reduce emission by 10 percent is to raise ξ_g by 10 percent. We thus pick this level for our reference magnitude in conducting simulation studies. We also experiment with other magnitudes and find that the relationship with the size of magnitude and the elasticities is linear in general.[15]

There are several interesting results that contrast the model to conventional predictions. First,

14. The national reduction target was disaggregated into Provincial level targets, which vary from 0 percent to 30 percent.

15. More precisely, the elasticity is weakly concave, with slightly larger elasticity when the policy magnitude is smaller.

as indicated in panel (a) of Figure 1, the elasticity of industrial emission is greater than -1. This means that if the $\xi^g_{Beijing}$ rises by 10 percent, Beijing's industrial emission is only reduced by 9.59 percent. As equation (29) implies, it is not theoretically obvious whether the elasticity of industrial emission is larger or smaller than -1, because it depends on how aggregate production G_n and manufacturing share $Y_{M,n}/G_n$ changes in response to ξ^g_n. Note that the nominal GDP (G) of Beijing responds positively to the stricter environmental regulation as shown in panel (i). In this case, a positive scale effect offsets the direct effect of increased ξ^g, and that results in an elasticity of industrial emission greater than -1. The positive scale effect of the regulation in this case coincides with the increased employment (thus in-migration) of skilled and unskilled workers to Beijing as shown in panels (d) and (e). This is an effect that cannot be predicted by the models without mobility of production factors (Copeland and Taylor 2004).

Regarding the propagated effect to cities outside of Beijing, panel (a) of Figure 1 shows an interesting contrast to the standard theoretical prediction of the PHE. If a pollution haven emerges, strengthening the environmental regulations in Beijing will cause an increase of emissions somewhere outside of Beijing, through the relocation of polluting industry to areas with relatively less stringent environmental policies. However, as shown in panel (a), the elasticity is everywhere negative, which means that the PHE does not take place here. The reduced emission from Beijing is not offset by increased emissions in other places. The environmental impact is even amplified by the reduced emission outside of the city, induced by Beijing's local policy. The reason for this can be seen in panels (d) and (e), that depicts the elasticities of the labor supply of skilled and unskilled workers, respectively. Beijing attracts both types of labor through the strengthened regulations, with a higher magnitude for skilled labor (0.099 for skilled compared to 0.073 for unskilled). Policy changes in Beijing therefore slightly attract labor from almost all over China, and contract the scale of production scale in places other than Beijing, as panel (i) suggests. Furthermore, as seen in panel (j), the composition effect which is the share of manufacturing production in total production decreases everywhere including outside of Beijing. These structural changes in scale and composition ensure the reduction of emissions everywhere in China, in response to policy changes in Beijing.

To understand the reasons why these spillover effects in labor supply and production structure emerge, we need further elaboration. First, a comparison of panel (g) and (h) reveals that skilled worker real wage respond in a opposite way as unskilled worker real wage. For the skilled workers, the real wage decreases in Beijing and increases almost everywhere outside of that city. Conversely, the unskilled worker's real wage increases in Beijing but decreases in other cities. The SEE (*spatial equilibrium effect*) works here. Skilled workers put more weight on air quality than unskilled workers as our estimated coefficients satisfy $\xi^k > \xi^u$, consistent with the assumption in (1). Due to this, the improvement in air quality in Beijing is large enough for skilled workers to compensate for the decline in real wages there. As in panel (l), the influx of skilled workers is associated with the decline in service price in Beijing which contributes to raise the real wage of the unskilled worker (note that the nominal unskilled wage is fixed by assumption). Then, both skilled and unskilled labor partially relocate to Beijing, and drive down production outside Beijing. Furthermore, the increase in ξ^g in Beijing raises the unit production cost of manufacturing there as in (10), which has spatial spillover effect on the manufacturing price index as in panel (k). This affects manufacturing production costs everywhere in China because the sector uses manufacturing intermediates as its inputs, making the response of the composition effect negative everywhere in China as in (j). These complex but rich relationships among the variables all work together to influence how our environmental variables are determined.

For price indices, note that the magnitude of the manufacturing price change is slightly smaller in the regions surrounding Guangdong Province and Shanghai, that are close to the international port. Due to better access to international markets, these areas trade less (in terms of share) with Beijing in the initial equilibrium. Therefore, the impact of unit cost increase in Beijing due to stricter regulation is mitigated. Panel (l) shows the elasticity of services prices, P_S. Only 'own' elasticity is negative while the others are positive. This is consistent with the responses of labors in panels (e) and (f). The services sector in Beijing benefits from the increased labor supply that drives down wages, while other cities will be affected by the reduced labor supply, as well as increases in the manufacturing price index as this is an input in the sector.

In summary, the economic implication of a unilateral policy change in our model is thus substantially different from the traditional PHE world. Stricter regulations in Beijing do not raise industrial emissions in other cities. Furthermore, higher $\xi^{g}_{Beijing}$ is not an economic burden for Beijing, while causing a slight damage to outside cities.

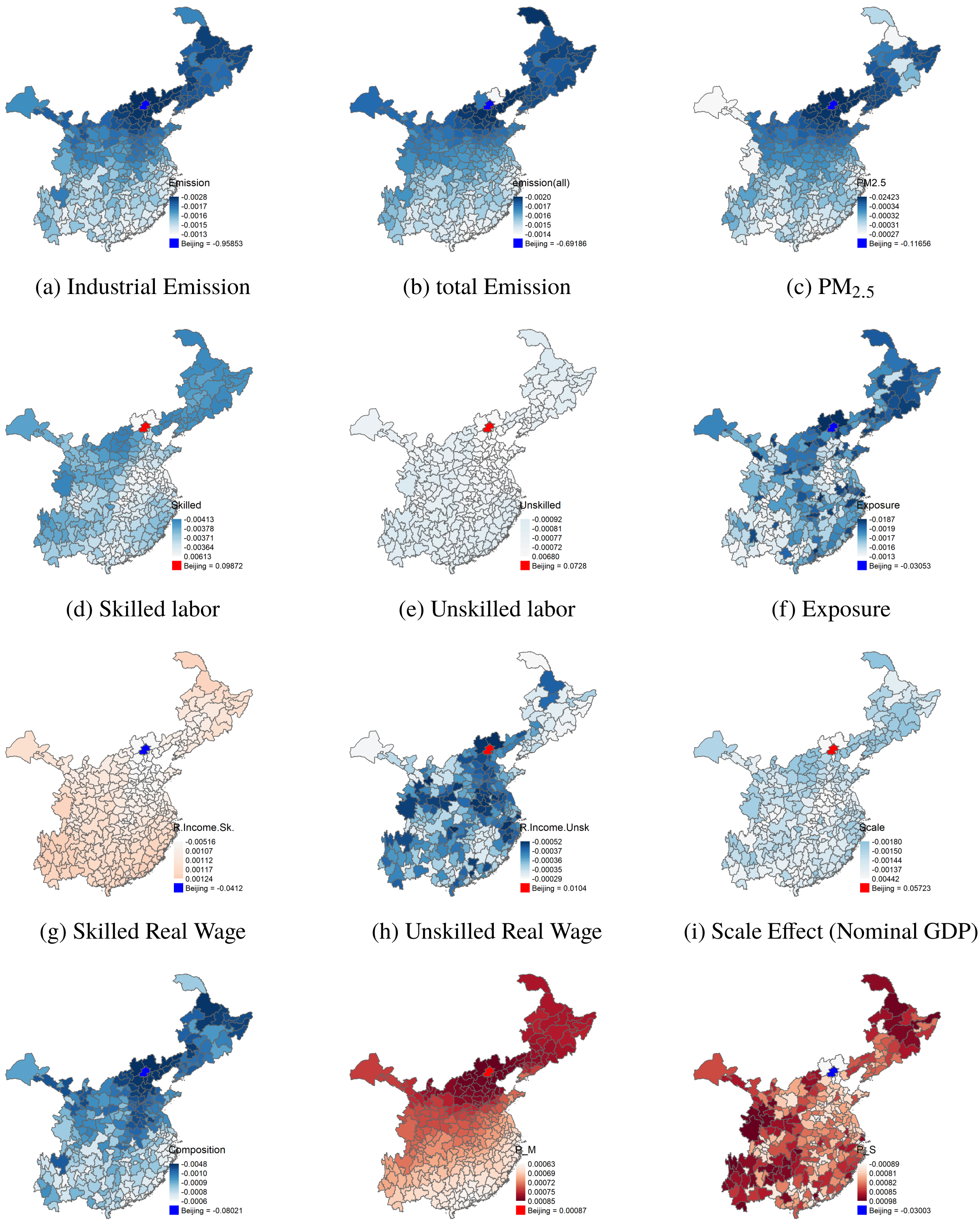
4.2 Where the Shock Originates Matters

By comparing the results of the same exercise for other epicenters of the shocks, namely Wuhan and Deyang, we examine whether these spatial patterns of the impact are universal. Figure A.4 shows the results for the city of Wuhan, the capital city of Hubei Province located in the central part of China. Figure A.5 shows the same for Deyang, a city in Sichuan Province. The spatial patterns of the propagation are fairly contrasting. As the panel (a) of Figure A.4 depicts, a policy shock in Wuhan reduces the industrial emission of neighboring cities. However, as the distance from the origin grows, the magnitude of elasticity shrinks more rapidly than the case of Beijing, reaching close to zero in the middle distance from Wuhan. Then, the elasticity again declines (magnitude increases) slightly when going much further. In contrast to Beijing, the emission elasticity is no longer monotonic with respect to the distance from Wuhan, showing an inverted V-shaped curve. The example of the shock from Deyang, in Figure A.5, shows a more exaggerated picture. In panel (a), the policy shock in Deyang is sown to cause a PHE in cities relatively closer to Deyang and the color turns red, except for a few direct neighbors.

4.3 Sensitivity to the Model's Key Assumptions

The model is different from the standard approach used to study the impact of local pollution control policy on national or global economies in three aspects. First, it allows for the production factor (workers) migration between cities. Second, workers care not only for their economic welfare but also environmental quality. Finally,it explicitly adds international trade to a domestic trade model. We ask what are the roles of these assumptions in determining the observed spatial

Figure 1: Illustration of the Spatial Effect of Policy Shocks from Beijing



(a) Industrial Emission
(b) total Emission
(c) $PM_{2.5}$
(d) Skilled labor
(e) Unskilled labor
(f) Exposure
(g) Skilled Real Wage
(h) Unskilled Real Wage
(i) Scale Effect (Nominal GDP)
(j) Composition Effect
(k) Manufacturing Price (P_M)
(l) Services Price (P_S)

Source: Author

Note: The maps depict elasticities computed against 10% change in the regulation parameter of Beijing ($\xi^g_{Beijing}$). Red colour indicates the positive computed elasticities, while the blue indicates the negative ones. The midpoint of the color palette is set to zero.

Table 2: Counterfactual Models

Feature	NMTW	NTW	NW	Benchmark
Domestic Migration	x	o	o	o
International Trade	x	x	o	o
Preference for Air Quality	x	x	x	o

Source: Author

Note: This table compares the features of the four models. "o" indicates that the model considers the feature as one of model's key mechanisms. If "x", the model treats the feature as restricted to zero.

effects.

To examine how sensitive the results on these assumptions, we compare three counterfactual models as explained below. Table 2 summarizes the features of the models we compare. Firstly, NMTW is a no-migration, no-trade, and no-welfare effect model. This counterfactual assumes that workers do not move from their current city, that trade takes place only within China, and that air pollution does not harm worker's welfare. Note that this is equivalent to a domestic trade version of the model of Eaton and Kortum (2002) with pollution as a regulated production input. The NTW (no-trade and no-welfare effect) model relaxes NMTW by allowing domestic migration. But, international trade is still ruled out, meaning that the geographical scope of migration and trade is only within the domestic arena. The third counterfactual, NW, introduces international trade. Through this change, goods gain a wider scope of mobility than workers because they become mobile across international borders.

Figure 2 shows the features of the four models using the results of simulation for a unilateral 10 percent increase in Beijing, by setting $\widehat{\xi^{g}_{Beijing}} = 1.1$ while keeping it to 1 for the others. Panel (a) compares the elasticity of Beijing's industrial emissions to its own policy change. All elasticities are negative and close to -1. Panel (b) plots the relationship between the city's distance to Beijing and its elasticity for each of four models. The red is for the NMTW model. Elasticity is negative for the cities near to Beijing then turns positive as the distance grows. This normal domestic trade model shows that the pollution haven effect (PHE) occurs in space. The negative elasticity nearby cities corresponds to the effects on the manufacturing price index captured in the panel (c). Due to the linkage through costly trade, the price index (i.e. input price) of the nearby cities increases more than that in the distant cities, pushing the polluting production to relatively further locations. If domestic migration is allowed, the graph for the NTW model in blue shows that the curve becomes steeper than the case of the NMTW. The decline in real income near Beijing due to increases in the price index and the reallocation of manufacturing make the worker migrate to cities further from Beijing. Migration flow outward from the Beijing area makes the response of emissions more elastic than in the case of MNTW. Then, introducing international trade shifts the MTW curve down, as the graph for the NW model (in green) shows. By introducing international trade, firms in China face price competition with foreign firms. Stricter regulation in Beijing increases input costs in China through the increases in the price index, P_M, with a larger magnitude than in the foreign market. This decreases China's competitiveness in manufacturing and reduces the production scale of manufacturing in the cities in China. As a result, the elasticity of emission for the NW model is lower than for the NTW model, and the area with negative elasticity expands. Finally, adding the preference for air quality to the NW model delivers our benchmark model. As we can observe from panel (b), introducing this preference substantially reduces the slope of the emission elasticity with respect to the distance from Beijing. In the benchmark model, both skilled and unskilled workers care about air quality when choosing a residential location. Since Beijing and nearby areas reduce emission and pollution, both skilled and unskilled labor migrate toward Beijing. This shrinks the scale of production outside the Beijing area, and offsets the PHE by the increase in the price index.

In contrast to the NTW model where tougher environmental regulation works as a *centrifugal* force on skilled labor, in the benchmark model it is a *centripetal* force. On the other hand, note that tougher regulation is always a centripetal force for unskilled labor. This happens due to the two substitutions that unskilled labor has between skilled labor and emissions. A tougher regulation of emission raises the price for emission, thus the factor demand for production shifts to demand more labor. However, due to the higher labor supply elasticity of skilled labor

($\eta^k > \eta^u$), skilled labor moves more sensitively in response to changes in the real wage, under the NW setting where they do not care about air quality. Unskilled labor is therefore a substitute for both emissions and skilled labor in the production of manufactured good and services.

In summary, the assumptions on migration and international trade play important roles in determining the behavior of the model. Allowing for migration or not in the model, or incorporating the welfare effect of pollution for workers, will significantly affect the degree of "distance decay" of the elasticity of emissions with respect to a cities' distance from the epicenter city. Disregarding the migration or welfare effect of air pollution might lead overstatement of the local impact of stringent pollution control policies. The migration of workers may work to mitigate such local impacts, especially if they care about pollution as studied by Chen, Oliva, and Zhang (2017) and Freeman et al. (2017). Ignoring international trade may also lead to an exaggeration of the local effects of regulation and the potential of the pollution haven effect by missing the channel of foreign demand.

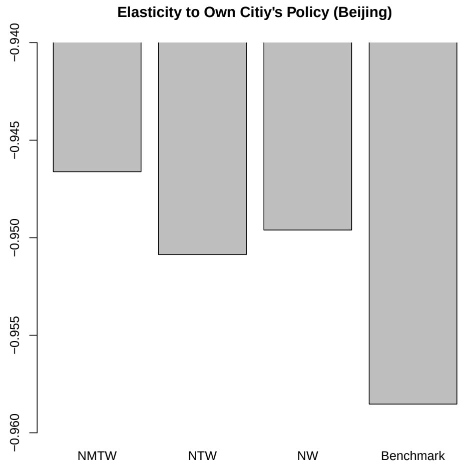
4.4 Comparing Aggregate Impacts of Local Policy

The spatial impact of local environmental policy differs with the location of any change that occurs. This suggests that the impact of local policy on aggregate outcomes may also vary depending on where the policy change happens. To show this, Figure 4 depicts the elasticities of the aggregate variables with respect to a local 10 percent increase in pollution control policy. The color and darkness of each map represent the sign and the magnitude of the elasticity of the national aggregate of the outcome variables with respect to this increase in the regulatory parameter ξ_n^g in each city.[16]

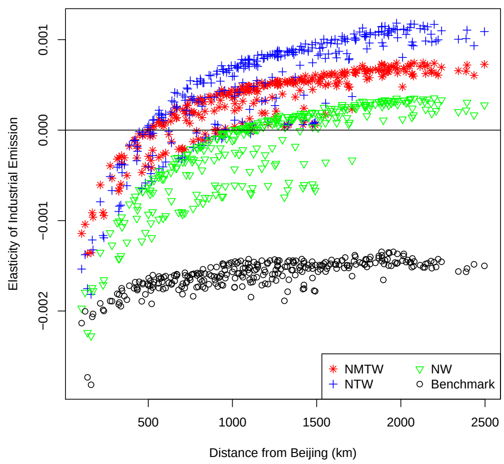
The elasticity of the aggregate emissions is depicted in panel (a). The elasticity is in fact highly correlated with the size of emissions from each city, with a correlation coefficient of -0.999. This is consistent with the previous observation we examined in the case of local policy in Beijing (and other two cities), where the elasticity of local emissions to policy in its own city

16. Average exposure to air pollution is average $PM_{2.5}$ concentration weighted by share of population.

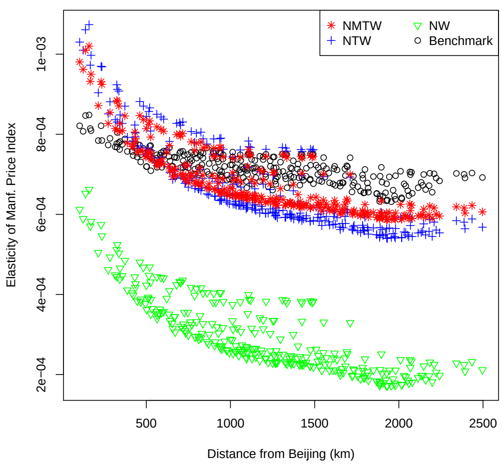
Figure 2: Model Comparison



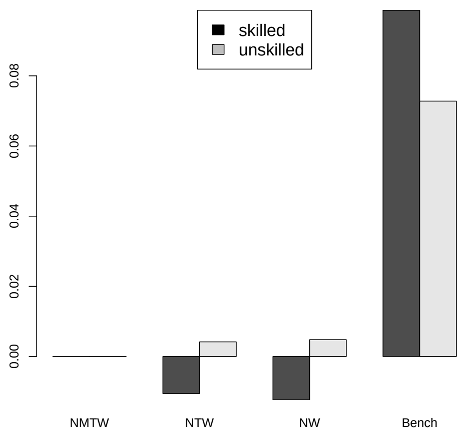
(a) Own-city Elasticity of Emission



(b) Distance and Elasticity of Emission



(c) Distance and Elasticity of P_M

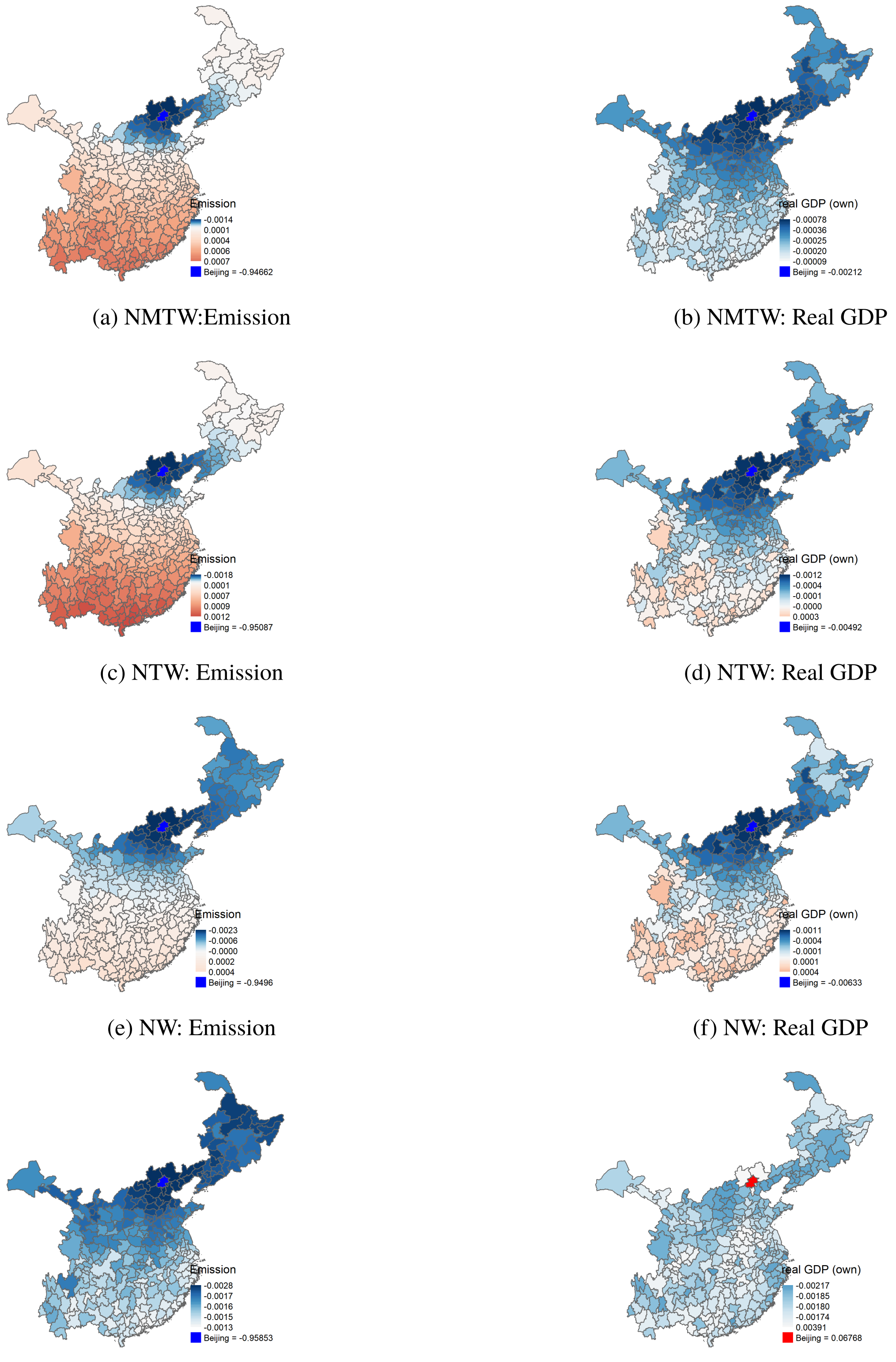


(d) Own-city Elasticity of labor

Source: Author

Note: Panel (b) and (c) depict the relationship between the distance from the city that the policy shock (environmental regulation) originates in (i.e. Beijing) and the elasticity of industrial emissions (b) or the price index (c) to the shock, comparing the benchmark model and three counterfactual settings, NMTW, NTW, and NW.

Figure 3: Counterfactual Models (Elasticities of Emission and Real GDP w.r.t. Regulation Shock in Beijing)



(a) NMTW:Emission

(b) NMTW: Real GDP

(c) NTW: Emission

(d) NTW: Real GDP

(e) NW: Emission

(f) NW: Real GDP

(g) Benchmark: Emission

(h) Benchmark: Real GDP

Source: Author

Note: The maps compares the four different models assuming the same policy shock (10 percent increase in ξ_n^g of the city n) happens in Beijing.

is close to -1, while the magnitude of the elasticity of the cities outside of the epicenter city is far smaller than one, as shown in panels (a) and (b) of Figure 2. Figure 4 panel (b) shows the elasticity of the nationwide average exposure to air pollution, calculated as the change of population weighted average of $PM_{2.5}$ concentration from the baseline. As shown in panel (a) and (b), emission and exposure elasticities are everywhere negative. There is no case where stricter policy in a city causes an aggregate increase in emissions or exposure to pollution. Despite the fact that there are cities such as Wuhan and Deyang where stricter regulation causes an increase of emissions in other cities, this PHE is not large enough to exceed the direct effect on the reduction of pollution in the epicenter and nearby cities.

The impact on aggregate economic variables is less straightforward. Panel (c) of Figure 4 illustrates how aggregate nominal GDP changes in response to strengthened pollution control policy in a city. Interestingly, there are 40 cities out of 296 whose increases in regulatory strength lead to a positive change in aggregate GDP. These cities tend to concentrate on the eastern coast where the most densely populated cities in China locate, such as Beijing, Tianjin, Shanghai, and Guangzhou locate. As confirmed in panel (i) of Figure 1, a unilateral change of regulatory strength in a city will increase the nominal GDP of its own and nearby cities while slightly reducing that of others. For those 40 cities with positive elasticities of aggregate nominal GDP, the positive effects on GDP of its own and nearby cities surpasses the negative effects for the others. Panel (d) depicts the impact on aggregate real GDP. This elasticity is highly correlated with that for the nominal GDP. For this case, there are 36 cities whose real GDP elasticity is positive. If environmental regulation is strengthened in one of these 36 cities, it will contribute to overall economic growth.

The economic impact of policy tends to favor unskilled workers more than the skilled. This is shown from the decomposition of the elasticity of real GDP into the effects on skilled and unskilled real incomes as in panel (e) and (f). Panel (e) and (f) reveal that skilled and unskilled workers face different consequences in terms of national average real income. For the skilled workers, national average real wage declines in most cases, except for 13 cities which are mainly located in the western and northern peripheries. On the contrary, the average real income of the unskilled increases if policy change takes place in the majority of coastal cities. There are a total of 108 cities that show the positive elasticity of average unskilled real wages.

Panels (g), (h), and (i) show the welfare elasticities with respect to the tightening of policy in each of 296 cities. The average welfare shown in panel (g) is calculated as the weighted average of skilled and unskilled welfare shown in (h) and (i).

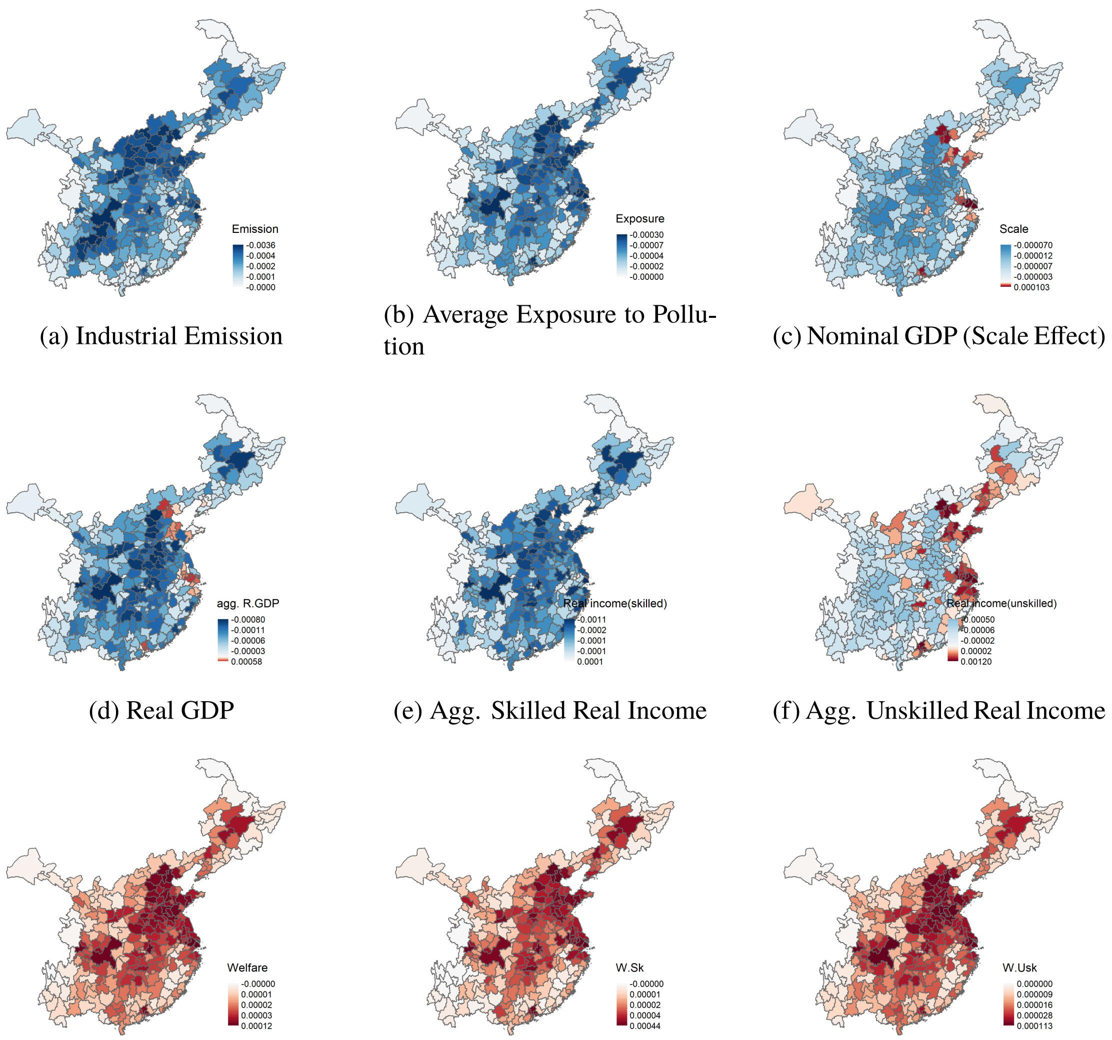
5 Quantifying the Impact of National Level Policies

In the previous section, we examined the model's comparative statics of a unilateral policy change in a single city. The model also allows us to study the impact of pollution control policies under more realistic situations. Since the 11th Five-Year Plan (FYP), the government of China has set national level reduction targets of major pollutants. For example, in the 11th FYP that covers years from 2006 to 2010, a 10 percent reduction in aggregate SO_2 emissions to the level of 2005 was set as the target. To achieve this nationwide target, a complex political process is followed to assign the decomposed targets to provincial and prefecture level administrations as their responsibilities for reduction. These regional targets are not uniform. Richer and populated areas have been assigned stricter targets, and the provincial targets vary from 0 percent to 30 percent during the 11th FYP (Stoerk 2017).

In what follows, we examine the impact of control policies at the national scale and the implications of different strategies on how to allocate reduction responsibilities across space. More specifically, we focus on the case where China tries to reduce aggregate (the national sum of) industrial emissions by 10 percent, reflecting the policy context in the 11th and 12th FYP, as discussed in the previous subsection. To reduce aggregate emission by 10 percent, how should the central government allocate reduction responsibilities across regions?

To answer this question, we compare the following six hypothetical responsibility allocations that achieve 10 percent reduction in aggregate emissions. In the model, our policy variable is ξ_n^g.

Figure 4: Comparing Aggregate Impacts across Epicentres (Benchmark Model)



(a) Industrial Emission (b) Average Exposure to Pollution (c) Nominal GDP (Scale Effect)

(d) Real GDP (e) Agg. Skilled Real Income (f) Agg. Unskilled Real Income

(g) Average Welfare (h) Skilled Welfare (i) Unskilled Welfare

Source: Author
Note: The maps depicts the elasticity of the national aggregate of the variable of interest with respect to 10 percent increase in ξ_n^g of the city n.

Table 3: Targeting Strategies

	Name	Weighting variable (x)	Constant (μ_x, mean and CI)**
(1)	all	Equally weighted ($x_n = 1, \forall n \in C$)	0.1039 [0.1038, 0.1040]
(2)	zm	Industrial emission	0.0277 [0.0275, 0.0278]
(3)	popden	Population density	0.1089 [0.1075, 0.1102]
(4)	Rin_u	Elasticity of average unskilled real income*	0.0802 [0.0759, 0.0844]
(5)	WELF	Elasticity of average welfare*	0.0498 [0.0495, 0.0500]
(6)	TP	Inverse of time to nearest international port	0.1099 [0.1078, 0.1121]

Source: Author

Note: * Weight is zero for cities with negative elasticity.

** "Constant" (μ_x) for the equation (32) in the third column is calculated as a result of simulation. The square bracket in the third column shows the confidence interval of the estimated μ_x

As in equation (28), this parameter is an exogenous factor determining the Pigouvian emission tax ζ_n charged to industrial firms in city n. In the following policy experiments, we compare different ways to set the reformed policy $\xi_n^{g'}, \forall n$ so that the new equilibrium generates 10 percent less aggregate emission compared to the original equilibrium. There could be infinitely many options in how to set $\xi_n^{g'}$ to achieve an aggregate 10 percent reduction in emission. To simplify the discussion, we model the six policy allocation strategies as follows.

Let x_n denote the weight assigned to city n with $\sum_{n \in C x_n} = 1$. Then, the reformed pollution control policy for the city n, $\xi_n^{g'}$, satisfies:

$$\frac{\xi_n^{g'}(x)}{\xi_n^g} = 1 + \mu_x x_n \tag{32}$$

where μ_x is a constant. Equation (32) implies that city n's new regulatory parameter ($\xi_n^{g'}$) is $100 \times \mu_x x_n$ percent higher than its original, ξ_n^g. We then call the distribution of x_n across $n \in C$ the allocation "strategy" of the policy change to achieve the targeted national reduction in emissions. Table 3 summarizes the hypothetical strategies for our experiment; these are explained below. The simplest reference strategy is to assign the same magnitude of policy change to all the cities, which is called the "all" strategy. In this case, $x_n = 1/N, \forall n$. Regarding the constant, μ_x, we search for the value that achieves a 10 percent decline in aggregate emissions by iterating the equilibrium calculation until the aggregate emission reduction converges to the target. For this "all" strategy, the average of μ_{all} equals 0.1039, which means that all cities increase ξ^g by 10.39 percent to achieve 10 percent reduction in aggregate emissions.

One possible way to differentiate the allocation of reduction responsibility across cities is to assign higher weights to those cities where the problem is more serious. The second and third strategies are examples of this. The second strategy "zm" adjusts the weight, x_n, equal to city n's industrial emissions in the observed equilibrium, as of 2010 in our exercise. This ensures that large emitters face more stringent tightening of the regulations. While this strategy intuitively seems to be an efficient way to reduce aggregate emission, it is not obvious whether it is superior to other strategies in terms of welfare and economic outcomes. The third strategy, "popden", is another example of a strategy to assign targets according to a current observable conditions. In this case, we consider that the central government tries to prioritize cities with large affected populations. Then, it sets x_n equal to n's population density.

Instead of referring to the observed city characteristics, suppose that the central government knows the elasticity of aggregate outcomes with respect to local unilateral policy change in each city, as summarized in Figure 4. The fourth and fifth strategies utilize these known elasticities for unilateral policy intervention to cities. Suppose that the central government wants to achieve reduction targets without reducing the economic benefits of low income people. The "Rin_u" strategy intuitively aligns to this desire of the central government. This strategy assigns the weight according to the elasticity of average real incomes of unskilled workers that is depicted in the panel (f) of Figure 4. There are many cities whose tightening of regulations negatively affects the average real income (those in blue in the map). We set the weight for these cities at zero. In the "WELF" strategy, we assign a weight equal to the elasticity of the average welfare as shown in panel (g) of Figure 4, because higher welfare gains are expected from the policy. We also add a strategy, "TP", that assigns the weight (x_n) according to the inverse of the travel time to the nearest international port from the city.

As revealed in the analyses on the unilateral policy change in a single city in the previous section, workers' preferences for air quality play an important role in determining the spatial impact of policy. Although we use estimated values for these parameters that are quite similar to an existing study by Chen, Oliva, and Zhang (2017), the sensitivity of the simulation results to different parameter values should be checked. We thus conduct a parametric bootstrap using the estimation results for ξ^t, similar to Faber and Gaubert (2019). Specifically, we sample the alternative parameter values from a normal distribution with a mean equal to the point estimate and a standard deviation equal to the standard error of the estimate (adjusted by the delta method). This bootstrap procedure is executed 100 times. For each trial, we calculate the changes in the equilibrium outcomes for six different strategies and stack the results to obtain the mean effect and its confidence interval.

Simulation Results The simulation results for the six targeting strategies summarized in Table 3 are shown in Figure 5. Panel (a) compares the impact on skilled worker welfare across the six strategies. Black graphs show the average and the 5 percent to 95 percent confidence interval as a percentage point change, simulated using the benchmark model. For all strategies, the impact on the skilled welfare is positive on average. The lower bound of the confidence interval at 5 percent is negative for all six strategies, suggesting that the welfare effect of the pollution control policy to reduce national emissions by 10 percent on the skilled labor is volatile with respect to the choice of parameter ξ^k that captures the preference of skilled workers for better air quality. Among the six strategies we examine, "Rin_u" strategy has a relatively higher average impact, but its variation is much larger compared to the other five strategies. We assume that the "Rin_u" strategy increases regulation a lot in a limited number of cities while keeping other cities from changing their level of environmental control. The result of the "Rin_u" strategy shown in panel (a) suggests that concentrating control intervention in a limited number of locations may deliver higher welfare gains on average, but that this outcome can be more sensitive to the unknown preference parameters.

Panel (b) depicts the impact on the unskilled worker's welfare. The average impact is positive for all strategies. What is more, for each of the six strategies, the entire confidence interval stays on the positive side. Thus, pollution control policy is in general beneficial for the unskilled, and its sign is less sensitive to the preference parameter than for the case of the skilled worker.

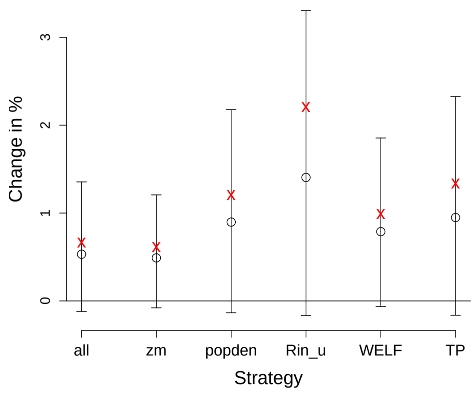
Panels (c) and (b) show more clear contrasts of outcomes between the skilled and unskilled. While the average real income of the skilled workers always declines under stricter pollution control policy, unskilled workers are always better off from such changes. For both skilled and unskilled workers, the magnitude of impact is the largest for the "Rin_u" strategy, while they are the most sensitive to the parameter values. As shown in panel (e), strengthening pollution control slightly reduces real GDP, but the magnitude is small and sometimes not substantially different from zero. The "Rin_u" strategy shows the outstanding sensitivity of this effect with respect to the choice of parameter values compared with other strategies, with a slightly positive average effect. Exposure to pollution will surely decline with the policy intervention, as shown in panel (f). Concentrating intervention to limited locations as in the "Rin_u" strategy will achieve the largest decline in exposure to pollution.

For all the panels, the red cross mark shows the average impact in the case where international trade is shut down. By comparing the cases with and without international trade, we can see that international trade pushes the impacts that favor the unskilled workers. Without international trade, the benefits for skilled workers shift up while those for unskilled workers shift down. This is especially so for the average real income of unskilled workers, as this is negative when international trade is absent while it is positive with trade.

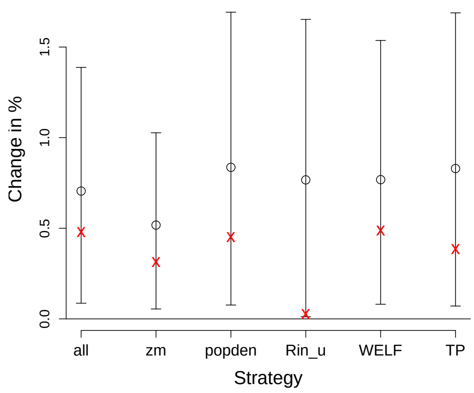
6 Conclusion

This paper develops a spatial equilibrium framework with endogenous air pollution to quantitatively study the impact of pollution control policies on welfare, economic, and environmental

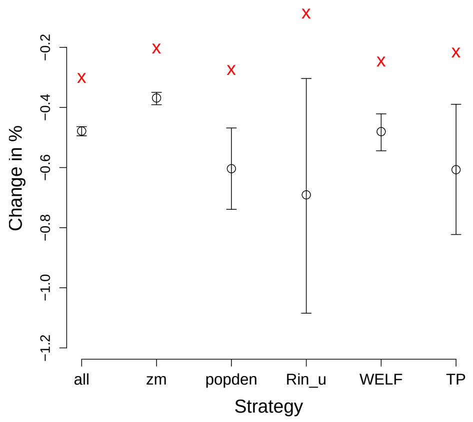
Figure 5: Comparing Strategies across the Models



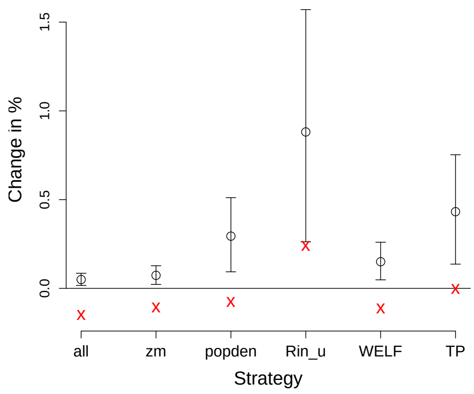
(a) Skilled Workers' Welfare



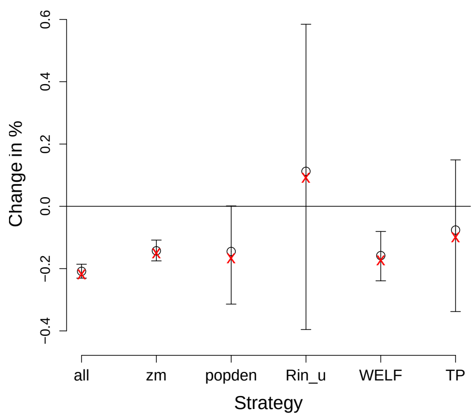
(b) Unskilled Workers' Welfare



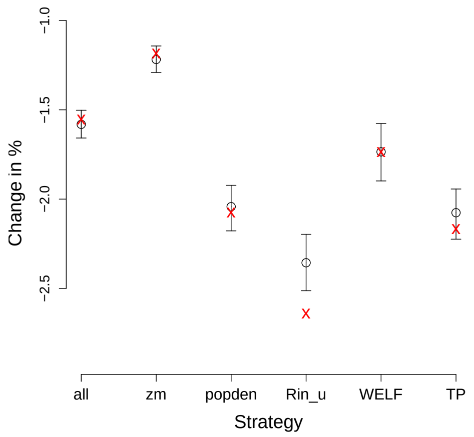
(c) Skilled Worker's Real Income



(d) Unskilled Worker's Real Income



(e) Real GDP



(f) Average Air Pollution Exposure

Source: Author
Note: These graphs depict the bootstrap mean and 5 percent confidence interval of the impact of nationwide policy to reduce aggregate emissions by 10 percent, as a percentage change of concerned outcome variables, across the six different targeting strategies. The black circle shows the mean of the effect and the lines stretching out from the circle shows the confidence interval. The red cross mark shows mean of the impact when assuming China is a closed country.

outcomes at regional and national scales. We calibrate the model to the Chinese economy's situation in 2010 at the level of prefecture-level cities. Some of the important parameters are estimated by exploiting the model's equilibrium conditions. To the best of our knowledge, this is the first attempt to explicitly incorporate endogenous air pollution into a quantitative spatial equilibrium framework. In our model, pollution control regulation is costly for firms as it may cause a reallocation of polluting industries to regions with more lax regulations, while this PHE can be (partially) offset by migration of workers who value air quality as a residential amenity.

We conduct a series of hypothetical simulations to study the implications of our theoretical model in a realistic setting. This approach allows the study of how a unilateral change of environmental policy in a single city can affect the city itself and other cities in China. In contrast to conventional trade-environment models, our spatial equilibrium framework with worker migration exhibits some cases where local environmental regulation delivers a positive economic benefit, even though regulation imposes additional costs on firms. Furthermore, in some cities, an increase in the local regulatory level may bring a positive economic return in terms of aggregate real GDP. These results emerge due to worker demands for better environmental quality and to let them migrate to an area where air pollution is reduced. In such cases, stricter regulation works as a *centripetal* force that attracts workers to the regulated regions, which coincidentally expands the scale of economic production.

Our approach is not free from shortcomings. First is that our discussion rests only within a static framework, ignoring the implication of dynamic changes. While our model can be regarded as a description of a steady state that will be reached in the long-run, this does not exclude the possibility that the observed results may not hold if dynamics are taken into account. Another caveat lies in the simplification of environmental quality into a single air pollution measure. While environmental quality has many dimensions, in the present paper we only care about ambient quality. Other important dimensions, such as water quality, soil quality, noise, radioactive pollution, biodiversity, and scenic beauty, are not covered. Moreover, within the category of the ambient pollution, the argument is simplified to where local air pollution can be represented by a single measure, $PM_{2.5}$ concentration. There are other important forms of air pollution such as nitrogen oxides, carbon monoxide, sulfur dioxide, and PM_{10} (which is a fine particulate matter that is greater than $PM_{2.5}$). We also miss the emission of global pollution that destroy the ozone layers and cause greenhouse gas effects, such as chlorofluorocarbons and carbon dioxide.

However, our primary interest is in that local air pollution that directly affects people's health and their economic behavior, including their choice of residential location. $PM_{2.5}$ is one of the most commonly known pollutants that directly affects human lung and cardiovascular systems. Furthermore, its concentration is closely linked to other pollutants that have similar effects on human health. Therefore, we believe that focusing on $PM_{2.5}$ is a reasonable generalization to avoid overcomplexity and to overcome data limitations, without causing serious biases in our analysis.

A Appendix

A.1 An Algorithm to Obtain Counterfactual Equilibrium using Changes

This appendix describes a practical procedure to solve the counterfactual equilibrium of the model using the "change," which is the ratio of the counterfactual equilibrium value of variable x to that of its original (observed, current equilibrium value).[17] We denote the change of variable x as $\widehat{x} = \frac{x'}{x}$, where x' is the counterfactual value of variable x. The following discussion summarizes the procedure for solving exogenous changes in trade cost $\widehat{\tau_{ni}}$, manufacturing productivity, $\widehat{A_{M,n}}$, services productivity, $\widehat{A_{S,n}}$, and/or strength of local pollution control $\widehat{\xi_{g,n}}$. Note that we do not have to know the levels of unobserved exogenous variables consistent with the current equilibrium, $A_{M,n}$, $A_{S,n}$, and $\xi_{g,n}$.

1. Initial guess on factor price changes (skilled wage and Pigouvian tax for pollution), $\widehat{w_n^k}$ and $\widehat{\zeta_n}$

2. Solve for $\widehat{P_{M,n}}$ and $\widehat{P_{S,n}}$ consistent with $\widehat{w_n^k}$ and $\widehat{\zeta_n}$ using

$$\widehat{c_n} = \left[\widehat{w_n^k}^{\gamma_M^k} \widehat{P_{M,n}}^{\gamma_M^M} \widehat{P_{S,n}}^{\gamma_M^S} \right]^{1-\delta} \widehat{\zeta_n}^{\delta} \tag{33}$$

$$\widehat{P_{M,n}}^{-\theta} = \sum_i \pi_{ni} \widehat{\tau_{ni}}^{-\theta} \widehat{c_i}^{-\theta} \widehat{A_{M,i}}^{\theta} \tag{34}$$

$$\widehat{P_{S,n}} = \widehat{A_{S,n}}^{-1} \widehat{w_n^k}^{\gamma_{S,n}^k} \widehat{P_{M,n}}^{\gamma_{S,n}^M} \tag{35}$$

3. Using the price vectors obtained in the previous step, update the trade shares according to:

$$\widehat{\pi_{ni}} = \frac{(\widehat{\tau_{ni}} \widehat{c_i})^{-\theta} \widehat{A_{M,i}}^{\theta}}{\widehat{P_{M,n}}^{-\theta}} \tag{36}$$

4. Using the vectors of price change obtained by the previous step, update the general price

17. This approach was first proposed by Dekle, Eaton, and Kortum (2008), and has been widely used in the literature.

index $\widehat{P_{T,n}}$ and expenditure share $\widehat{\chi_{j,n}}$, $j \in F, M, S$ as follows:

$$\widehat{P_{T,n}}^{1-\rho} = \chi_{F,n} + \chi_{M,n}\widehat{P_{M,n}}^{1-\rho} + \chi_{S,n}\widehat{P_{S,n}}^{1-\rho} \tag{37}$$

$$\widehat{\chi_{F,n}} = \frac{1}{\widehat{P_{T,n}}^{1-\rho}}, \quad \widehat{\chi_{M,n}} = \frac{\widehat{P_{M,n}}^{1-\rho}}{\widehat{P_{T,n}}^{1-\rho}}, \quad \widehat{\chi_{S,n}} = \frac{\widehat{P_{S,n}}^{1-\rho}}{\widehat{P_{T,n}}^{1-\rho}} \tag{38}$$

5. The expenditures on manufacturing and services goods, as well as their production in the counterfactual equilibrium are given by:

$$E'_{M,n} = \widehat{\chi_{M,n}}\chi_{M,n}\left(\widehat{w_n^k}w_n^k L_n^k + w_n^u L_n^u\right) + (1-\delta)\gamma_M^M Y_{M,n} + \gamma_{S,n}^M Y_{S,n} \tag{39}$$

$$Y'_{M,i} = \sum_n E'_n \pi'_{ni} \tag{40}$$

$$Y'_{S,i} = E'_{S,i} = \widehat{\chi_{S,n}}\chi_{S,n}\left(\widehat{w_n^k}w_n^k L_n^k + w_n^u L_n^u\right) + (1-\delta)\gamma_M^S Y_{M,n} \tag{41}$$

6. Update land price and emissions:

$$\widehat{r_n}^{1-\omega} = \frac{\widehat{\zeta_n}}{\widehat{\xi_{g,n}}} \tag{42}$$

$$\widehat{Z_{M,n}} = \frac{\widehat{Y_{M,n}}}{\widehat{\zeta_n}} \tag{43}$$

$$\widehat{Z_{R,n}} = \widehat{\chi_{M,n}}\widehat{r_n} \tag{44}$$

7. Then update the level of pollution:

$$D'_n = f(\bar{X})\left(Z_{M,n}' + Z_{R,n}'\right)^{\kappa} \tag{45}$$

8. Update labor force distribution for each type $t = \{k, u\}$:

$$\widehat{L_n^t} = \frac{\left(\widehat{e_n^t}\widehat{w_n^t}\widehat{P_{T,n}}^{-\alpha}\widehat{r_n}^{\alpha-1}\right)^{\eta}}{\sum_j \frac{L_j^t}{L_C^t}\left(\widehat{e_j^t}\widehat{w_j^t}\widehat{P_{T,j}}^{-\alpha}\widehat{r_{n'}}^{\alpha-1}\right)^{\eta}} \tag{46}$$

where

$$\widehat{e_n^t} = \frac{\exp(-\xi^t D_n')}{\exp(-\xi^t D_n)} \tag{47}$$

9. The skilled wage and total value added (GDP) are then updated by:

$$w_n^{k\prime} = \frac{\left[(1-\delta)\gamma_M^k + \delta\right] Y_{M,n}' + \gamma_{S,n}^k Y_{S,n}'}{\widehat{L_n^k} L_n^k} \tag{48}$$

and

$$G_n' = w_n^{k\prime} \widehat{L_n^k} L_n^k + w_n^u \widehat{L_n^u} L_n^u \tag{49}$$

10. Obtain new values for factor prices $\widehat{w_n^k}$ and $\widehat{\zeta_n}$ from:

$$\widehat{w_n^k} = \frac{w_n^{k\prime}}{w_n^k} \tag{50}$$

$$\widehat{\zeta_n} = \widehat{G_n}^{1-\omega} \widehat{\xi_{g,n}} \tag{51}$$

11. Iterate 2 to 10 until values converge.

A.2 Details of the Data

Population and value added Our unit of analysis is those prefecture-level cities or counties that are directly under Provinces plus the four direct-administered municipalities of China as of 2010, within the Eastern half of the mainland China. This area basically overlaps with the historical territory of the Han dynasty (B.C. 206 - A.D. 220). Four provinces/autonomous regions, Inner Mongolia, Xinjiang, Qinghai, Tibet, and islands (such as Hainan Province) are dropped from the analysis. We make this choice because the western part of China dropped from the analysis is economically and demographically very sparse compared to the Eastern half, holding only 4.3 percent of total population while occupying more than 51 percent of the land area. We thus follow other studies such as Baum-Snow et al. (2018) in keeping our focus on the Han part of China. The area consists of 296 geographical units (270 prefecture-level cities and 26 counties directly under the Provinces). The Economic variables, such as the value added of primary, secondary, and tertiary industries, are taken from the *China City Statistical Yearbook* and *China Region Economy Statistical Yearbook* of 2011 that report their values as of 2010. Employment variables are constructed benefiting from the online supplementary materials of Baum-Snow et al. (2017) that originally aggregated the *2010 Population Census* at the level of counties. In the county-level aggregate of the census, the employment in primary, secondary, tertiary industries is provided. These are summed to the level of prefecture cities as the employment of three industry strata to obtain the aggregate labor force in the location. Then, we compute the amount of skilled labor by multiplying the total labor force with the share of population with at least a senior high school degree. The remaining labor is treated as unskilled.[18]

$PM_{2.5}$ Concentration The yearly $PM_{2.5}$ concentration is computed from raster images provided by Donkelaar et al. (2016), which are available from `fizz.phys.dal.ca/~atmos/martin/?page_id=140`. This is the estimated level of $PM_{2.5}$ concentration on the surface using the satellite image of aerosol. Raster images cover all the ground surface of the earth annually since 2000. A growing number of recent studies use this set of satellite images of $PM_{2.5}$ to recover the spatio-temporal variations of China's air pollution, especially for obtaining the spatially disaggregated situation before 2014 when China started detailed and frequent official reporting of air pollution.[19] There are a few advantages in using this satellite data. Until the early 2010s, China had reported situations of local air pollution for only a limited number of cities (only around 100 cities). Since the satellite images by Donkelaar et al. (2016) are the raster information of $0.01° \times 0.01°$ mesh containing the annual average concentration of $PM_{2.5}$, covering all over the world sine 1998, the researchers basically calculate the level of pollution of

18. Combes et al. (2019) define skilled labor as employees received at least technical or vocational training after completing senior high school, which may be stricter than our definition of the skilled labor. The country-level aggregates we use do not report the the number of people enrolled in technical or vocational schooling after senior high school, while the number of people with college degree is available. Therefore, we do not know from our data how many of those who completed senior high but not college received additional education such as technical and vocational training.

19. Examples include Chen, Oliva, and Zhang (2017) and Freeman et al. (2017).

an arbitrary geographical unit. Secondly, as argued by Chen et al. (2013), the official data on air pollution seem to be incorrect because of manipulation by the local authorities. Satellite images are generally considered to be more reliable. The spatial distribution of the annual average concentration of $PM_{2.5}$ within each prefecture-level unit is depicted in Figure A.1.

Pollutant Emission Inventory We rely on satellite based data on the emission of the ambient pollutants that are the primary sources of $PM_{2.5}$. We use the MIX database from MEIC[20], maintained by the researchers from the leading universities in China. The database provides the gridded (0.25°× 0.25°) emission inventory of major pollutants such as SO_2, NO_x, and primary $PM_{2.5}$. The monthly gridded emission inventory is used to construct the annual sum of emission in each grid and vectorize the raster data by calculating the mean level of emission for each prefectural polygon.

Particulate matter is formed primarily through combustion of fuels as well as natural sources. In addition, secondary particulates emerge from other pollutants such as SO_2 and NO_x, then finally form the particulate matter observed in the air. When we estimate (26) to obtain coefficient κ and $f(\tilde{X}_n)$, we follow Sun et al. (2017) who assume that the $PM_{2.5}$ concentration in n consists of the local emission of primary $PM_{2.5}$ as well as SO_2 and NO_x emissions that contribute as secondary sources. For this purpose, therefore, we exploit the emission inventory data of these important pollutants. Importantly, the MEIC emission inventory provides the local emission of those pollutants from four different sources; industry, power generation, traffic, and residences. This allows us to disentangle the emissions from the production side and the residential side, denoted by Z_M and Z_R in the model, respectively. In practice, we calibrate Z_M by the sum of the emissions of SO_2, NO_x, and primary $PM_{2.5}$ from industry and power generation. For Z_R, we use the sum of the same set of pollutants from the traffic and residential sources. Table A.1 summarizes the emissions of each pollutants from the four different sources.

20. `http://www.meicmodel.org/index.html`

Table A.1: Emission of Major Pollutants from Sources (unit: kilotonne)

	Power	Industry	Residential	Transport
SO_2 (sum)	7,079.0	19,134.7	3044.9	202.1
(mean)	247.5	66.9	10.6	0.7
NO_x (sum)	7,753.8	9,954.0	990.0	6,158.2
(mean)	27.1	34.8	3.5	21.5
Primary $PM_{2.5}$ (sum)	746.4	5,430.0	4,138.0	442.9
(mean)	2.6	19.0	14.5	1.5

Based on gridded emission inventory dataset from MEIC (`http://www.meicmodel.org/index.html`)

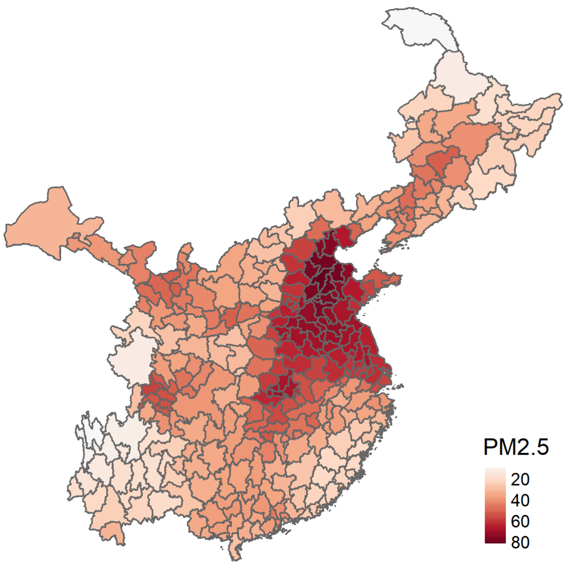
Other variables As detailed below, we use a set of control variables in the estimation of labor supply elasticity, η^t, and parameter of disutility from pollution ξ^t. Our identification strategy use the same instrumental variables and control variables as Baum-Snow et al. (2018), such as population as well as the share of high school graduates in 1982, and so on. We thus benefit again from their online appendix. In addition, we also add climate control variables such as precipitation and temperature since these can simultaneously affect the level of pollution and people's residential choice, which is equivalent to the labor supply in the model. For these climate variables, we use the satellite images from "TerraClimate" database (Abatzoglou et al. 2018). [21] From the raster files of monthly records, we calculate the annual average precipitation and temperature within the boundary of each prefecture-level unit.

A.3 Spatial Distribution of Pollution in China

Figure A.1 illustrates the spatial distribution of $PM_{2.5}$ (particulate matters smaller than 2.5 micrometers) concentration in the populated Eastern half of China ("Han" China) in 2010. $PM_{2.5}$ is small particle that is one of the most harmful to the human body. In the area around Zhongyuan (Central Plain) in the South of Beijing, and including Tianjin, Hebei, Henan, and Shandong Provinces, the level of pollution is collectively very high. In this area, the long-

21. The data can be downloaded from `http://www.climatologylab.org/terraclimate.html`

Figure A.1: $PM_{2.5}$ Concentration (μ/m^3) in 2010



Source: Author
Note: Based on Donkelaar et al. (2016), the mean level of $PM_{2.5}$ within the boundary of each city is depicted.

term population-weighted exposure to $PM_{2.5}$ concentration exceeds $64\mu g/m^3$.[22] This area also contains China's major megalopolises where densely populated cities are clustered across a large space to accommodate more than 300 million people. By this overlap of pollution and population, huge numbers of people face significant health risks. The welfare consequences of this unhealthy spatial distribution are seriously undesirable.

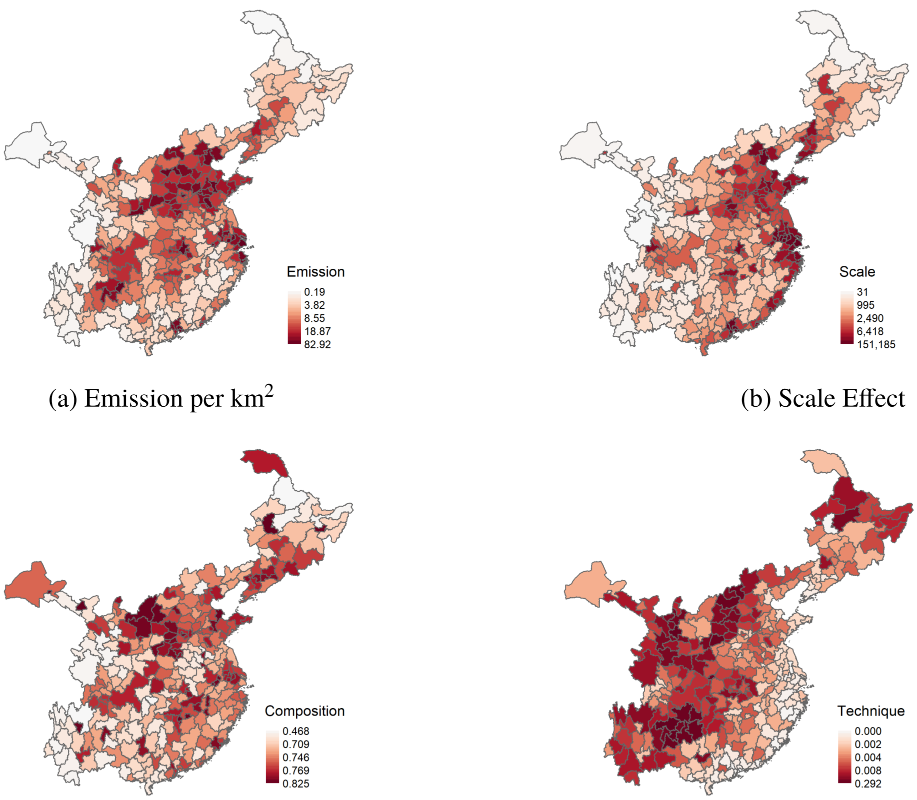
As seen in the introduction, the spatial distribution of $PM_{2.5}$ concentration is not uniform across space. Spatially uneven distribution can also be found for the anthropogenic emission of major ambient pollutants. The maps in Figure A.3 display the spatial patterns of anthropogenic emission for the three major ambient pollutants, sulfur-dioxide (SO_2), nitrogen-oxides (NO_x), and the primary emission of $PM_{2.5}$, produced from human activities.[23] From a visual examination, the spatial patterns are highly correlated between that of emissions and that of the $PM_{2.5}$ concentration level.

The spatial distributions of pollution and emission shown above are highly associated with the distribution of economic activities across space. In short, the agglomerated regions generate a lot more pollutants and are significantly severely polluted. To see this, we follow the decomposition proposed by Grossman and Krueger (1995) that separates amount of emissions into (i) scale effect, (ii) composition effect, and (iii) technique effect. Scale effect is the amount of total economic production (per area) from a region of a city. Composition is the share of output value from polluting industry. In our case, this refers to the output share from the secondary sector (manufacturing and power generation). The technique effect equals to the emission intensity of that polluting industry, which is the amount of emissions per unit of output value. This reflects the environmental efficiency of the polluting industries in the region. Furthermore, in models like this paper presents, the technique effect is proportional to the inverse of the Pigouvian emission tax imposed on a unit emission, as will be discussed later. More specifically, the decomposition

22. Long-term population-weighted exposure is the average of annual average $PM_{2.5}$ concentration weighted by residential population. For reference, the U.S. standard for the long-term population-weighted exposure is $12\mu g/m^3$.

23. Primary $PM_{2.5}$ refers to the emission of particulate matters with a diameter of less than 2.5 micron that is generated directly from the combustion of fuels and other materials. This is different from the concentration of $PM_{2.5}$ within a given mass of outdoor air.

Figure A.2: Decomposition of Industrial Emission



(a) Emission per km^2

(b) Scale Effect

(c) Composition Effect

(d) Technique Effect

Source: Author

Note: The emission amount is the sum of SO_2, NO_x, and primary $PM_{2.5}$ from industrial and power generation sources. See Section A.2 for the details of the data definition. Scale effect is in 10,000 RMB per km^2 and technique effect is in kilo-tonnes per km^2. All the data are from 2010. See Section A.2 for the details of data used.

is expressed as an identity for the total industrial emission from region i as follows:

$$\underbrace{Z_i}_{\text{emission}} = \underbrace{Y_i}_{\text{scale}} \times \underbrace{\frac{Y_{M,i}}{Y_i}}_{\text{composition}} \times \underbrace{\frac{Z_{M,i}}{Y_{M,i}}}_{\text{technique}} \tag{52}$$

where $Z_{M,i}$ is the total emission from polluting sectors (say, manufacturing) in i, Y_i is the total economic output in i including sectors other than polluting sector (such as services). $Y_{M,i}$ is the polluting sector's output. This decomposition helps us to capture which of the factors of economic scale, composition of production, or environmental efficiency (regulation) is more relevant than others in explaining the spatial distribution of pollution and emission.

Figure A.2 collects the maps showing the decomposition of the industrial emissions that make up the major part of China's anthropogenic pollutant emissions. Panel (a) illustrates the industrial emissions, the sum of SO_2, NO_2, and primary $PM_{2.5}$ emissions from manufacturing and power generation. Panels (b), (c), and (d) show the decomposition of Panel (a), based on the identity (52). Panel (B) shows the scale effect. Its spatial distribution overlaps with (a), suggesting that scale matters for these emissions. Cities with denser economic activity tend to emit larger amount of pollutants. Panel (c) is for the composition. Composition is also positively correlated with the emission. Emissions are likely in large cities with higher secondary sector shares. On the contrary, the distribution of technique effect shown in panel (d) does not overlap with that of emissions. Correlations of each of the three factors with emission are 0.775 (scale), 0.536 (composition), and 0.032 (technique), respectively, which supports the visual observation from Figure A.2 on the relevance of the scale followed by the composition, as well as the irrelevance of the technique effect. This is in contrast to the evidence on the development of U.S. manufacturing firms during recent decades, as illustrated by Shapiro and Walker (2018). They argue that in the U.S., the technique effect has dominated the overall trend in the emissions of air pollutants. However, note that the correlation between scale effect and technique effect is -0.606, meaning that emission intensity is lower where economic density is higher. This can also be confirmed from panel (b) and (d) of Figure A.2, where the scale shows a east-high west-low distribution, while the technique one is west-high east-low. In summary, the geographical distribution of pollutant emission and pollution in China largely overlaps with the distribution of economic density. Thus, economic agglomeration, especially industrial agglomeration, means agglomeration of pollution as well. While the environmental efficiency is expressed as the level to which the technique effect partially offsets the scale effect, it is not large enough to perfectly cancel out the scale and composition effect.

A.4 Calibration and Estimation

Bilateral trade cost between cities Bilateral trade cost between locations is not directly observable in our data. In general, there are two approaches to estimate bilateral trade cost from available data in the trade and geography literature. The first and traditional approach that has been mainly used in the international trade literature is to recover it by using the gravity equation with bilateral trade flow data (Head and Mayer 2004). The theory employed in this paper also yields a gravity equation that allows the implementation of this method. However, the key limitation of this method is data availability. While bilateral trade data between every pair of locations are required, these are largely unavailable for domestic trade. For China, Poncet (2003, 2005) and Tombe and Zhu (2019) are among the researchers using this approach. As the Chinese domestic trade flow matrices are provided only at the level of Provinces and for a limited number of years, their analyses are restricted to the Provincial level. The second method is to impute the trade cost using the travel time (or distance) between the pair of locations, as employed by Donaldson and Hornbeck (2016) and Baum-Snow et al. (2018). Typically, a shortest path algorithm (e.g. the Dijkstra Algorithm) is used to calculate travel time to reach from one place to another based on digital maps of transportation infrastructure networks. The calculated travel time matrix are converted into a bilateral iceberg trade cost matrix using the known parameters that pin down the relationships between the freight shipment time and the cost. Our focus on the prefecture-level analysis naturally rules out the first approach because there is no bilateral trade data at this level of granularity in China. Therefore, it is necessary to closely follow the data and methods employed by Baum-Snow et al. (2018) to recover the trade cost matrix.[24] Particularly, we benefit from the online appendix of Baum-Snow et al. (2018) and use the historical highway network digital maps as of 2010. The Dijkstra Algorithm is used to compute the shortest paths between each pair of cities.

International Trade Cost For international trade in the M sector goods, we assume that the trade cost for city i is the trade cost to reach its closest international port multiplied by the border effect. Let τ^j_{Xi} denote the trade cost between i and the RoW. Then, assume that $\tau_{Xi} = \tau_b \tau_{port(i)i}$, where, τ_b a common border effect and $\tau_{port(i)i}$ is the transportation cost to the closest port from i. τ_b can be recovered by applying the gravity equation as explained in Head and Mayer (2004), by using China's national exports $\mathcal{E}$, national imports $\mathcal{I}$,[25] total production of manufacturing goods in RoW, $Y_{M,X}$, and China's total expenditure on manufacturing goods E_C, as follows:

$$(\tau_b)^{-2\theta} = \frac{\mathcal{E}\mathcal{I}}{(Y_X - \mathcal{E})(E_C - \mathcal{I})} \tag{53}$$

With $\theta = 5$ as will be explained below, we obtain $\tau_b = 1.68$.[26]

Input shares and Wages Data on local skilled and unskilled wages are not available. However, the average wage in each sector at the national level is provided in *China Statistical Yearbook*. Average wage in a sector j, w_j is given by $w_j = \frac{w^k L^k_j + w^u L^u_j}{L^k_j + L^u_j}$. Noting that the production function in both the manufacturing and services sectors is Cobb-Douglass, $w^k L^k_j = \tilde{\gamma}^k_j V_j$ and $w^k L^u_j = \tilde{\gamma}^u_j V_j$ follow, where V_j is the value added of sector j and $\tilde{\gamma}^t_j = \frac{\gamma^t_j}{\gamma^k_j + \gamma^u_j}$, $t \in k, u$ is the type

24. Another novel approach, which has recently emerged, is to use the freight cost quotations provided by logistics companies. The advantages of using this approach to two other conventional approaches is detailed in Yang (2018).

25. According to the China Statistical Yearbook 2011, China's manufacturing exports in 2010 were 10,047 billion RMB and imports were 6,129 billion RMB. We implicitly assume the trade imbalance (positive net export) in manufacturing goods is offset by the net import of agricultural goods.

26. Baum-Snow et al. (2018) instead set $\tau_b = 1.15$ based on the review by Anderson and Wincoop (2004). This number could be too old to be consistent with the data in 2010, and does not necessarily reflect the situation of developing countries such as China.

t share in the value added. Using these relationships, we can compute the skilled labor share using:

$$\tilde{\gamma}_j^k = \frac{w^k(w_j - w^u)}{w^j(w_k - w^u)} \tag{54}$$

It is assumed that the agricultural sector employs only unskilled labor, hence the national agricultural wage is equal to the national unskilled wage w^u. Similarly, it is assumed that the financial intermediation sector employs only skilled labor and that the national skilled wage w^k equalises to the national wage rate in the financial intermediation sector. With these w^u and w^k, in addition to the wage rates in the sub-sectors shown in Table A.5, we can obtain the skilled labor share for each j. Among the sub-sectors whose average wage rates are available in the China Statistical Yearbook, one sub-sector ("Agriculture, Forestry, Animal Husbandry and Fishery") can be categorized as primary industry (F in the model), four sub-sectors ("mining," "Manufacturing," "Electricity," and "Construction") into secondary industry (M), and the remaining fourteen sectors into the tertiary (S) industry. Then, we compute the skilled labor share of the $J \in F, M, S$ industry is:

$$\tilde{\gamma}_J^k = \frac{\sum_{j \in J} w_j L_j \tilde{\gamma}_j^k}{\sum_{j \in J} w_j L_j} \tag{55}$$

Given the input shares of intermediate goods in production of the M and S industries, namely, γ_M^M, γ_M^S, and $\gamma_{S,n}^M$ in (7) and (14), the input shares of skilled and unskilled labor in these industries are given by $\gamma_M^t = \tilde{\gamma}_M^t(1 - \gamma_M^M - \gamma_M^S)$ and $\gamma_{S,n}^t = \tilde{\gamma}_S^t(1 - \gamma_{S,n}^M)$.[27]

At the prefecture-city level, we have neither sectoral wages nor skilled/unskilled wages. Instead, the value added in each of three industries, denoted here by $V_J, \forall J \in F, M, S$, is used. We then use the obtained labor shares and value added to recover the skilled and unskilled wages in city n by:

$$w_n^k = \frac{\frac{(1-\delta)\gamma_M^k + \delta}{(1-\delta)(1-\gamma_M^M - \gamma_M^S)} V_{M,n} + \frac{\gamma_{S,n}^k}{1-\gamma_{S,n}^M} V_{S,n}}{L_n^k} \tag{56}$$

27. From China's input-output table as of 2007 provided in *China Statistical Yearbook 2011*, we set $\gamma_M^M = 0.6859$ and $\gamma_M^S = 0.1004$, respectively.

$$w_n^u = \frac{V_{F,n} + \frac{(1-\delta)\gamma_M^u}{(1-\delta)(1-\gamma_M^M-\gamma_M^S)} V_{M,n} + \frac{\gamma_{S,n}^u}{1-\gamma_{S,n}^M} V_{S,n}}{L_n^u} \tag{57}$$

Expenditure share (α) We calibrate α using the expenditure shares of consumers provided in the China Statistical Yearbook 2011. On average, households in China spend 13% of their total expenditure on housing, thus we set $\alpha = 0.87$.[28]

The elasticity of trade with respect to trade cost (dispersion parameter θ) There are several studies that estimate trade elasticity θ. While the majority of these are in the context of international trade, it is possible to find a number of examples on how to apply these estimates in the study of domestic trade. Baum-Snow et al. (2018) set $\theta = 5$ while experimenting $\theta \in [3, 10]$. Tombe and Zhu (2019) sets $\theta = 4$. Bryan and Morten (2019) use the range 4 to 8 in the context of domestic trade in Indonesia, referring to Allen and Arkolakis (2014) who use the value of 8 and Bernard et al. (2003) who found that $\theta = 4$. Caliendo et al. (2018) analyze the heterogeneous impact of local productivity shocks to aggregate the U.S. economy using the Ricardian model of trade with disaggregated sectors. They employ the estimates of the trade elasticity of detailed sectors by Caliendo and Parro (2015) that study the welfare effects of NAFTA on the U.S. economy. While the elasticity varies a lot across sub-sectors, their main estimates of the aggregate level elasticity (including agriculture, mining, and manufacturing sub-sectors) range from 3.29 to 4.55. Gervais and Jensen (2019) estimate θ in the context of the U.S. domestic trade incorporating services sector trade, finding that the mean value of θ for manufacturing goods is 8.14. Faber and Gaubert (2019) choose $\theta = 6.1$ based on the estimates by Adao, Arkolakis, and Esposito (2018) as well as Head and Mayer (2014). In summary, there seems to be no consensus on the value of θ for domestic trade, but previous studies tend to choose values between 4 and 8. We take $\theta = 5$ following Baum-Snow et al. (2018).

28. This value is the same as Tombe and Zhu (2019) who also study the equilibrium in 2010.

Input share of pollutant emission (δ) Little is known about the value of δ, the input share of pollutant emission which is also the inverse efficiency of abatement technology. To the best of our knowledge, Shapiro and Walker (2018) is the only study that provides an estimate for δ consistently with a general equilibrium model with trade like ours. They estimate δs for detailed U.S. manufacturing sub-sectors using factory level abatement investment data covering a long period of time (1990s to 2008). While their estimates of δ greatly vary across the sub-sectors, they report an average for the manufacturing sector as a whole is $\delta = 0.011$. Since estimating δ for China is difficult with the currently available data as explained below, we use this value for the simulation analysis.

Data on abatement expenditure of Chinese manufacturing firms is not available at prefecture-level granularity. Therefore, it is impossible to choose and estimation strategy similar to that of Shapiro and Walker (2018). Another possible way to estimate δ for China is to use the ratio of emission levy revenue to manufacturing output, as equation (20), which is a way Shapiro and Walker (2018) actually avoid. If we assume that δ is constant across space, we can technically recover it only with nationwide total emission levy revenue and the value of industrial output. While official statistics of the emission levy revenue are available from the *China Environment Yearbook*, it should be noted that the levy revenue may cover only a fraction of the wide range of expenditure that the term $\zeta_i Z_{M,i}$ in (20) represents. In fact, the ratio of the total emission levy to industrial output in China is less than 0.00001. If the estimate of Shapiro and Walker (2018) for U.S. manufacturing firms is correct, this means that abatement efficiency of Chinese manufacturing firms is 100 times superior to that of the U.S. firms, which is simply incredible.[29] According to a dataset for international comparison by the OECD (`https://stats.oecd.org/Index.aspx?DataSetCode=ENV_ENVPOLICY`), the ratio of environment related tax to industrial

29. The system of environmental control is complicated. In China, along with emission levies on designated pollutants, the government sets the targets for reducing the aggregate emissions of selected pollutants. For achieving the target, local governments in China uses variety of policy instruments. For example, local governments sometimes order polluting plants to shut down or relocate. Polluting firms implicitly pay substantial costs for lobbying (or even bribing officials as reported by Rooij (2006)) in order to avoid such sanctions. Therefore, it seems appropriate to assume there is more implicit expenditure than actually observed as emission levies that the manufacturing firms in China spend for realising the observed combination of emission and production.

output is around 1 percent which can also support our choice of δ, even if the assumptions leading to this number are not clear.

Elasticity of substitution among three category of goods (ρ) There is only limited guidance in the literature on the appropriate value of ρ, the elasticity of substitution among the three categories of goods. As pointed out by Faber and Gaubert (2019), ρ should be smaller than the elasticity of substitution between the varieties within the same category of goods. In our case, this means that $\rho \le \theta + 1$ should be satisfied. We search for the value of ρ in this range such that the model derived consumption expenditure share of manufacturing goods at the national level is equal to the observed data. This exercise gives the value $\rho = 3.45$ that is used throughout the analyses in this paper.

labor supply elasticity (η^t) and disutility from pollution (ξ^t) We estimate the elasticity of labor supply of each type of worker (η^t) as well as the parameters of the welfare impact of pollution (ξ^t) that are consistent with our model. Equation (31) is estimated to recover η^t and ξ^t consistent with the model. The existing literature provides guidance on the identification concerns and possible solutions.[30] As discussed in Faber and Gaubert (2019), OLS estimation of labor supply elasticity, the coefficient on the real wage term, or aggregate real factor income $\ln \widetilde{W_n^t}$ in our case, can be downward biased due to unobserved confounding factors in labor demand and supply. In addition, estimates for ξ^t can also be biased because there is the possibility of omitted variable bias and reverse causality. For example, as the same as the estimate of the real wage term, unobserved labor demand shock can be either positively or negatively correlated with pollution, D_n, because that can cause more emission as well as strengthen regulations through the local government's endogenous response (28). Furthermore, local amenities consisting B_n^t, such as climate characteristics, may simultaneously affect D_n and L_n^t.

To address these identification concerns, we use the set of instruments and controls that Baum-Snow et al. (2018) use to estimate the causal impact of 2010 road infrastructure on prefecture's

30. See Faber and Gaubert (2019), Fajgelbaum et al. (2019), and Fajgelbaum and Gaubert (2019).

demographic and economic outcomes. They instrument 2010 road infrastructure measures by those of 1962. More specifically, in their main specification, their variables of interests are the log efficiency road unit and the log time to nearest international port, both reflecting infrastructure quality in 2010. The efficiency road unit is the length of road infrastructure weighted by average travel speed within a 450km radius of each prefecture minus the weighed road length within own prefecture. The time to the nearest international port is the shortest travel time to the closest international port out of nine candidates. They instruments these 2010 infrastructure variables by their 1962 counterparts, arguing that these instruments are exogenous to 2010 demographic and economic variables conditional on several historical and geophysical controls.[31] Based on Baum-Snow et al. (2018)'s argument, we instrument $\ln \widetilde{W_n^t}$ and D_n by these 1962 variables and an exogenous climate variable. The rationale for instrumenting $\ln \widetilde{W_n^t}$ is straightforward. 1962 infrastructure variables predict current employment, wages, and industrial composition well but they are not correlated with unobservable contemporaneous productivity and amenity shocks. The unobserved shocks that simultaneously affect 1962 infrastructure placement and contemporaneous productivity are assumed to be eliminated by the set of historical and geographical controls. For pollution, we instrument this with the SO_2 emission from power plants located in the upper-wind direction of the city. The constructed instruments are similar to the IV2 of Freeman et al. (2017). Instead of coal consumption by upper-wind thermal electricity plant, we use the emission of SO_2 by power plants, due to data availability. Our IV is the sum of SO_2 emission from power plants with in the 90 degree-sector of 500 km radius from the city, minus the emissions within own city.

The first stage results are shown in Table A.3. The three variables of interest, the level of $PM_{2.5}$ concentration, the log of $\widetilde{W^t}$ for $t = \{k, u\}$ are regressed on the same set of the instruments

31. Baum-Snow et al. (2018) justify that 1962 variables are exogenous to the contemporaneous shocks determining 2010 demographic and economic outcomes based on the historical context of China's road development during the pre-economic reform period. In 1962 when China was under the socialist planning economy before economic liberalisation in the 1980s, the roads were primarily designed to move agricultural goods between villages using non-motorised vehicles. Therefore, the road development then did not concerned the production and logistics for the manufacturing goods using late 20th century technologies. At the same time, despite not being designed for the motorised vehicles, the existence of 1962 roads provided the right-of-the-way for the alignment of the highways whose planning and construction started in 1990s.

and control variables. The three variables on the top of the table are the instruments.[32] Table A.4 shows the second stage results. The first two columns are for the OLS estimates, while the column (3) and (4) show the results of IV estimations. As expected, the OLS estimates on the real wage terms ($\ln \widetilde{W^t}$) are downward biased compared to the IV estimates. The implied values of η^t from our IV estimates are $\eta^k = 3.52$ and $\eta^u = 1.16$, respectively. Interestingly, our IV estimates on $PM_{2.5}$ are very close to the estimates of the impact of $PM_{2.5}$ level on the migration of skilled and unskilled labor by Chen, Oliva, and Zhang (2017) which are -0.0093 for skilled labor and -0.0047 for unskilled labor. Given these estimates, the implied values are $\xi^k = 0.013$ and $\xi^u = 0.0095$.

Coefficient of policy elasticity to GDP (ω) As in (28), the elasticity of pollution control policy with respect to GDP is $1 - \omega$. Taking the log of (28) and noting that $\zeta_n = \delta \frac{Y_{M,n}}{Z_{M,n}}$, we have

$$\ln \zeta_n = \beta_0 + (1 - \omega) \ln G_n + \ln \xi_n^g \tag{58}$$

We estimate ω by OLS estimation of (58). Endogeneity concerns come with any omitted variables that are simultaneously related to ζ_n and G_n. Specifically, the model implies two reverse causalities that flow from ζ_n to G_n. First, the lowered pollution that is induced by higher ζ_n will increase labor supply from the migration equation (30), then positively affect G_n. In contrast, high ζ_n increases the production costs in the manufacturing sector (10) and may contract total value added G_n. To address these concerns, we instrument $\ln G_n$ by the historical market access that is proxied by the 1962 road efficiency unit and the 1962 time to nearest port. Additionally, to control for any shocks that might be simultaneously correlated with 1962 infrastructure variables and $\ln \xi_n^g$, we include a Province capital dummy, an environmental priority city dummy, the historical level of pollution that is proxied by the level of $PM_{2.5}$ annual average concentration in 1999, the log of the distance to coast, and four variables that capture

32. Given that the 1962 log road efficiency unit is not significant for $\ln \widetilde{W^k}$ and $\ln \widetilde{W^u}$ as shown in Table A.3, we also estimate the version without this instrumental variable. The second stage results are qualitatively the same.

1982 demography, as shown in Table A.2. Provincial capital has specific political and economic importance and it is reasonable to assume that their status as Provincial capitals simultaneously affected the 1962 infrastructure placement as well as the unobserved shocks to the current environmental regulations captured in ξ^g. In our sample cities, there are 105 environmental priority cities whose environmental performance are reported in the annual *China Environment Yearbook*. Again, priority cities should have a specific shock in ξ^g which might be also correlated with the 1962 infrastructure variables if economic development after 1962 affected the probability of them being chosen as a priority city.

The results are shown in Table A.2. Our IV estimate on the log of GDP is 0.544 which implies that $\omega = 0.466$.

Elasticity of PM$_{2.5}$ to emission (κ) The relationship is specified as in (26). We estimate the logarithm of the equation by proxying D_n using the aerial concentration of PM$_{2.5}$($\mu g/cm^3$) and Z_n using the total emission of SO_2, NO_x, and the primary PM$_{2.5}$ emissions from both production and consumption sources (Z_M and Z_R). In turn, κ is estimated by OLS and the value obtained is $\kappa = 0.16$. The exponential of the constant term plus the residual recovers ξ_n^g.

Table A.2: Estimation of the Environmental Regulation Equation

	OLS	*IV*
	(1)	(2)
log of GDP, $[1-\omega]$	0.645^{***}	0.544^{**}
	(0.096)	(0.270)
Provincial Capital	−0.110	−0.073
	(0.170)	(0.207)
Priority City	-0.243^{***}	−0.207
	(0.093)	(0.132)
log of $PM_{2.5}$, 1999	0.103	0.129
	(0.100)	(0.125)
Log km to coast	-0.167^{***}	-0.182^{***}
	(0.029)	(0.052)
Log prefecture population, 1982	-0.468^{***}	−0.384
	(0.137)	(0.245)
Log city centre population, 1982	−0.099	−0.119
	(0.085)	(0.099)
Share of population with high school, 1982	0.174	0.249
	(0.366)	(0.395)
Share of population in manufacturing, 1982	0.507	0.811
	(0.501)	(0.852)
Constant	4.043^{***}	4.591^{**}
	(1.064)	(1.881)
Observations	283	283
R^2	0.523	0.520
Adjusted R^2	0.507	0.504

Source: Author

Note: Heteroskedasticity robust standard errors are given in the parentheses. In the IV estimation, the log of GDP is instrumented by log 1962 road efficiency unit and log 1962 time to nearest port as in Baum-Snow et al. (2018). *p<0.1; **p<0.05; ***p<0.01

Table A.3: First Stage Estimates for the Labor Supply Equation

	Dependent variable:		
	$PM_{2.5}$	$\ln \widetilde{W^k}$	$\ln \widetilde{W^u}$
	(1)	(2)	(3)
Log road efficiency unit, 1962	7.514^{***}	-0.057	-0.115
	(2.363)	(0.141)	(0.126)
Log time to nearest port, 1962	-2.715^{***}	-0.292^{***}	-0.222^{***}
	(1.002)	(0.060)	(0.053)
Log power plant emission in upwind	0.329^{**}	-0.003	-0.002
	(0.141)	(0.008)	(0.008)
Provincial Capital	4.586^{**}	0.615^{***}	0.452^{***}
	(2.253)	(0.135)	(0.120)
Log prefecture population, 1982	6.823^{***}	0.575^{***}	0.644^{***}
	(1.899)	(0.114)	(0.101)
Log city centre population, 1982	-2.048	-0.105	-0.131
	(1.493)	(0.089)	(0.080)
Share prefecture population with high school, 1982	1.253	0.833^{**}	0.750^{***}
	(5.420)	(0.324)	(0.289)
Share prefecture population in manufacturing, 1982	-22.326^{**}	3.175^{***}	2.273^{***}
	(8.841)	(0.529)	(0.471)
Log prefecture area	-9.017^{***}	0.117	0.080
	(1.431)	(0.086)	(0.076)
Log prefecture area	0.520	-0.085^{*}	-0.062
	(0.783)	(0.047)	(0.042)
Log km to coast	1.407^{***}	-0.016	-0.013
	(0.495)	(0.030)	(0.026)
West Region	-0.283	-0.185^{*}	-0.179^{**}
	(1.668)	(0.100)	(0.089)
East Region	2.973^{*}	0.070	0.071
	(1.653)	(0.099)	(0.088)
Log city centre roughness	-3.233^{***}	-0.002	-0.016
	(0.591)	(0.035)	(0.031)
Log prefecture roughness	-2.298^{***}	-0.035	-0.041
	(0.496)	(0.030)	(0.026)
Log precipitation	-0.007^{***}	-0.0004^{***}	-0.0003^{***}
	(0.002)	(0.0001)	(0.0001)
Log mean temperature	0.001	0.032^{***}	0.026^{***}
	(0.118)	(0.007)	(0.006)
Constant	15.944	-0.832	0.874
	(37.515)	(2.243)	(1.998)
Observations	283	283	283
R^2	0.772	0.742	0.740
Adjusted R^2	0.757	0.726	0.723
Residual Std. Error (df = 265)	8.072	0.483	0.430
F Statistic (df = 17; 265)	52.646^{***}	44.874^{***}	44.285^{***}

Source: Author
Note: Heteroskedasticity robust standard errors are in the parentheses. *p<0.1; **p<0.05; ***p<0.01

Table A.4: Estimating the Labor Supply Equation

	Dependent variable:			
	$\ln L_n^k$	$\ln L_n^u$	$\ln L_n^k$	$\ln L_n^u$
	OLS	*OLS*	*IV*	*IV*
	(1)	(2)	(3)	(4)
$\mathrm{PM}_{2.5}$, $[-\xi^t \eta^t/(\eta^t+1)]$	0.002	−0.001	−0.010**	−0.005
	(0.002)	(0.002)	(0.004)	(0.003)
$\ln \widetilde{W^k}$, $[\eta^k/(\eta^k+1)]$	0.706***		0.779***	
	(0.075)		(0.141)	
$\ln \widetilde{W^u}$, $[\eta^u/(\eta^u+1)]$		0.521***		0.537***
		(0.133)		(0.138)
Provincial capital	0.242***	−0.102	0.258***	−0.092
	(0.055)	(0.063)	(0.084)	(0.063)
Log prefecture population, 1982	0.370***	0.551***	0.458***	0.580***
	(0.069)	(0.100)	(0.096)	(0.100)
Log city centre population, 1982	−0.113***	−0.039	−0.142***	−0.047
	(0.041)	(0.036)	(0.045)	(0.036)
Share prefecture population, with high school, 1982	0.332**	−0.044	0.339*	−0.036
	(0.158)	(0.172)	(0.181)	(0.170)
Share prefecture population, in manufacturing, 1982	0.294	−1.091***	−0.415	−1.265***
	(0.332)	(0.386)	(0.590)	(0.424)
Log prefecture area	0.092**	0.004	−0.060	−0.040
	(0.042)	(0.042)	(0.066)	(0.055)
Log city centre area	0.029	0.011	0.042	0.014
	(0.022)	(0.021)	(0.026)	(0.021)
Log km to coast	−0.014	−0.007	0.018	0.002
	(0.013)	(0.014)	(0.021)	(0.014)
West Region	−0.134***	0.096*	−0.139**	0.093*
	(0.049)	(0.055)	(0.062)	(0.056)
East Region	−0.210***	−0.052	−0.169***	−0.038
	(0.039)	(0.039)	(0.047)	(0.040)
Log city centre roughness	0.031	0.042	−0.010	0.031
	(0.027)	(0.039)	(0.030)	(0.038)
Log prefecture roughness	0.022	−0.013	−0.005	−0.021
	(0.014)	(0.018)	(0.020)	(0.021)
Log precipitation	−0.0001***	−0.0001	−0.0002***	−0.0001*
	(0.00004)	(0.00005)	(0.0001)	(0.0001)
Log mean temperature	0.006*	0.005	0.004	0.005
	(0.003)	(0.003)	(0.004)	(0.003)
Constant	−3.062***	−1.473*	−2.324**	−1.284
	(0.863)	(0.817)	(0.981)	(0.824)
Observations	283	283	283	283
R^2	0.923	0.885	0.907	0.883
Adjusted R^2	0.918	0.878	0.902	0.876
Residual Std. Error (df = 266)	0.237	0.248	0.260	0.249
F Statistic (df = 16; 266)	199.438***	127.470***		

Source: Author
Note: Heteroskedasticity robust standard errors are in the parentheses. *p<0.1; **p<0.05; ***p<0.01

Table A.5: Imputed Skilled Share in the Labor Income Across Sectors

Detailed Sector	Categorization	Average Wage (Yuan)	Employment (10,000 people)	Imputed Skilled Share ($\frac{\gamma_j^k}{\gamma_j^k+\gamma_j^u}$)
Agriculture, Forestry, Animal Husbandry and Fishery	F	16717	375.7	0.000
Mining	M	44196	562.0	0.706
Manufacturing	M	30916	3637.2	0.366
Production and Distribution of Electricity etc.	M	47309	310.5	0.759
Construction	M	27529	1267.5	0.226
Traffic, Transport, Storage and Post	S	40466	631.1	0.633
Information Transmission, Computer Services	S	64436	185.8	0.956
Wholesale and Retail Trades	S	33635	535.1	0.457
Hotels and Catering Services	S	23382	209.2	0.000
Financial Intermediation	S	70146	470.1	1.000
Real Estate	S	35870	211.6	0.522
Leasing and Business Services	S	39566	310.1	0.614
Scientific Research, Technical Service	S	56376	292.3	0.878
Management of Water Conservancy, Environment	S	25544	218.9	0.127
Services to Households and Other Services	S	28206	60.2	0.257
Education	S	38968	1581.8	0.600
Health, Social Security and Social Welfare	S	40232	632.5	0.628
Culture, Sports and Entertainment	S	41428	131.4	0.653
Public Management and Social Organization	S	38242	1428.5	0.583

Source: Author

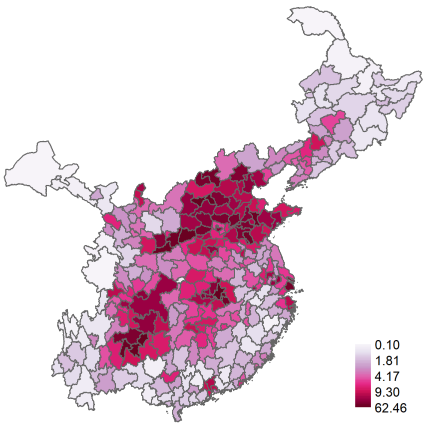
Based on China Statistical Yearbook 2011 (Table E0405 and E0415)

Categorization: F = Agriculture, M = Manufacture, S = Traded Services, H = Housing Services.

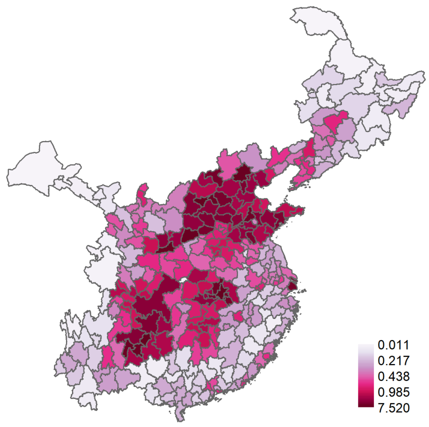
Agriculture assumed to employ 100% unskilled labor. We assume hotel and catering sector is the entry point sector for rural agricultural unskilled worker whose wage rate is at the indifferent level compared with agricultural wages taking urban living cost into account.

We assume that $w^u = w_{agriculture}$ and $w^k = w_{finance}$, where w^u is unskilled wage and w^k is skilled wage, respectively. Then, for given sector wage, w_j, the skilled workers share in labor income in the sector is imputed by $\frac{\gamma_j^k}{\gamma_j^k+\gamma_j^u} = \frac{w^k(w_j-w^u)}{w_j(w^k-w^u)}$.

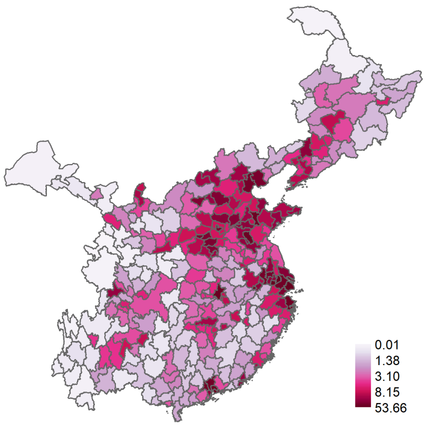
Figure A.3: Emission of Pollutants from Production and Consumption Sources



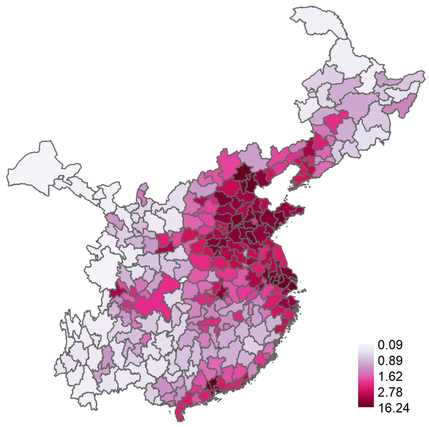
(a) **SO_2 from production (kilo-tonne/km^2)**



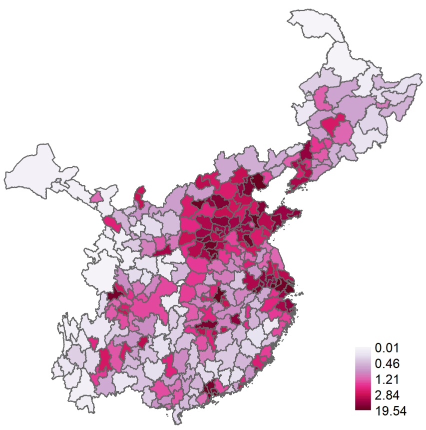
(b) **SO_2 from consumption (kilo-tonne/km^2)**



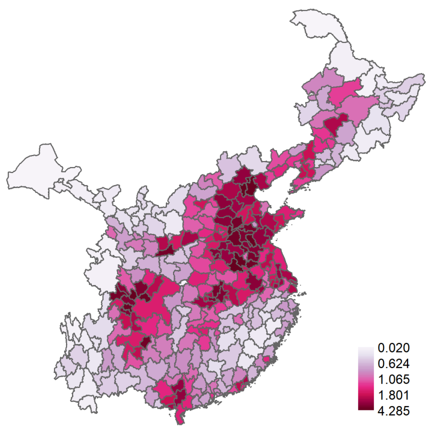
(c) **NO_2 from production (kilo-tonne/km^2)**



(d) **NO_2 from consumption (kilo-tonne/km^2)**



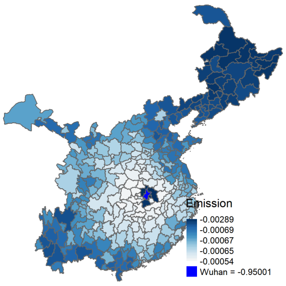
(e) **Primary $PM_{2.5}$ from production (kilo-tonne/km^2)**



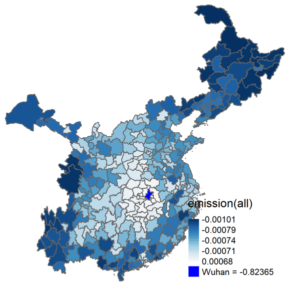
(f) **Primary $PM_{2.5}$ from consumption (kilo-tonne/km^2)**

Source: Author

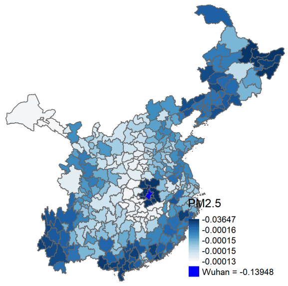
Figure A.4: Illustration of the Spatial Effect of Policy Shock from Wuhan



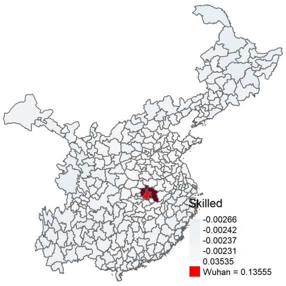
(a) Industrial Emission



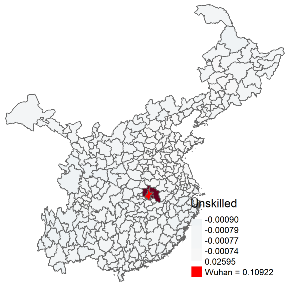
(b) total Emission



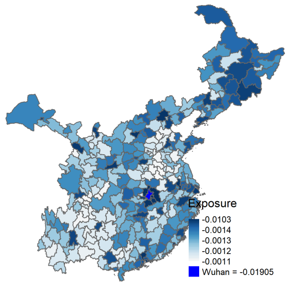
(c) $PM_{2.5}$



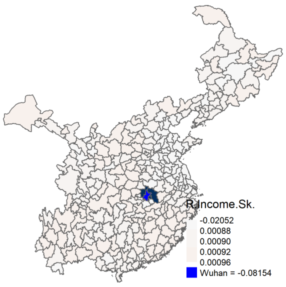
(d) Skilled labor



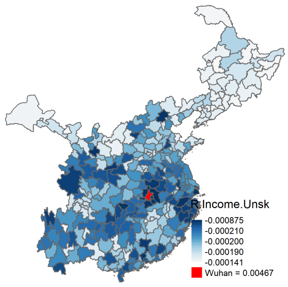
(e) Unskilled labor



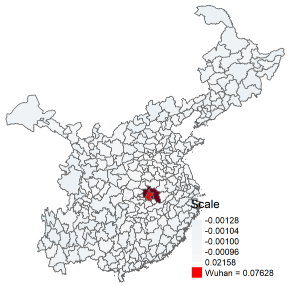
(f) Exposure



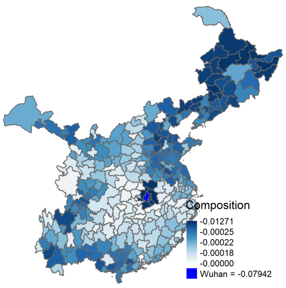
(g) Skilled Real Wage



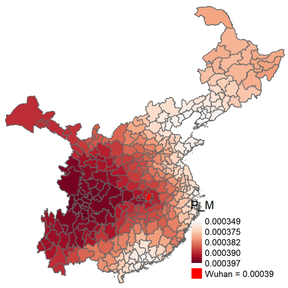
(h) Unskilled Real Wage



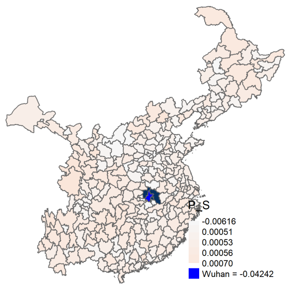
(i) Scale Effect



(j) Composition Effect



(k) Manufacturing Price (P_M)

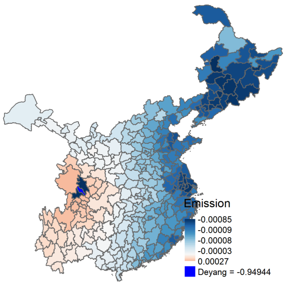


(l) Services Price (P_S)

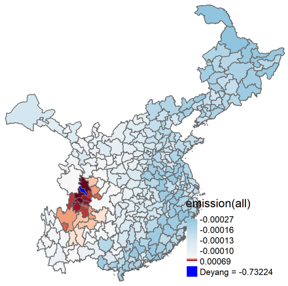
Source: Author

Note: The maps depict elasticities computed against a 10 percent change in the regulation parameter of Wuhan (ξ^g_{Wuhan}). The red color indicates the positive computed elasticities, while the blues indicate negative ones. The midpoint of the colour palette is set to zero.

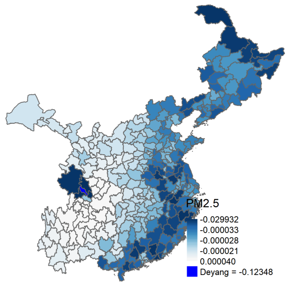
Figure A.5: Illustration of the Spatial Effect of Policy Shock from Deyang



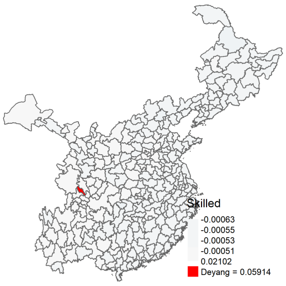
(a) Industrial Emission



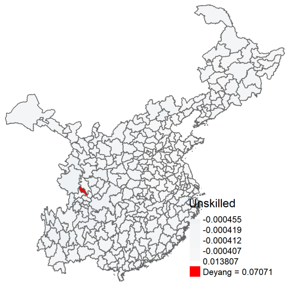
(b) total Emission



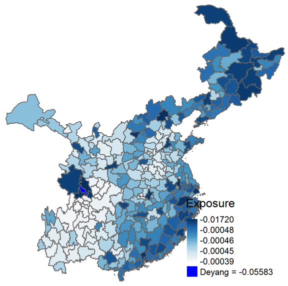
(c) $PM_{2.5}$



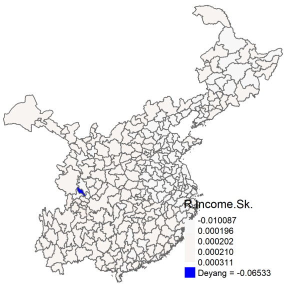
(d) Skilled labor



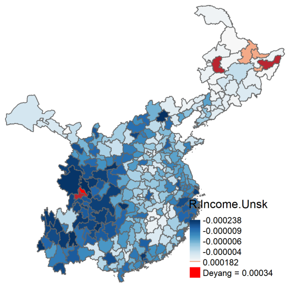
(e) Unskilled labor



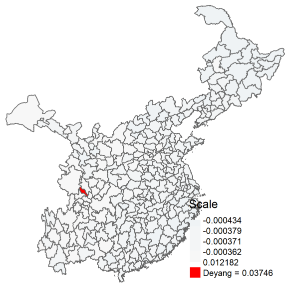
(f) Exposure



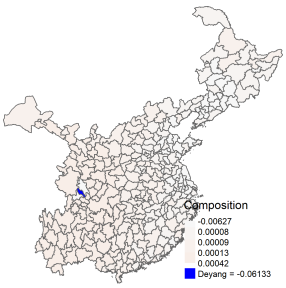
(g) Skilled Real Wage



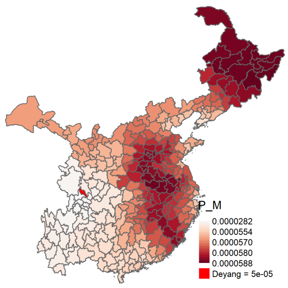
(h) Unskilled Real Wage



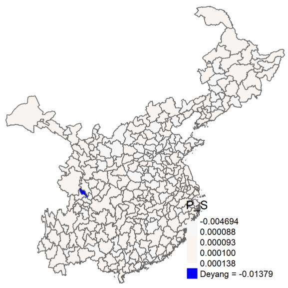
(i) Scale Effect



(j) Composition Effect



(k) Manufacturing Price (P_M)



(l) Services Price (P_S)

Source: Author
Note: The maps depict elasticities computed against a 10 percent change in the regulation parameter of Deyang (ξ^g_{Deyang}). The red color indicates the positive computed elasticities, while the blues indicate negative ones. The midpoint of the colour palette is set to zero.

References

Abatzoglou, John T., Solomon Z. Dobrowski, Sean A. Parks, and Katherine C. Hegewisch. 2018. "TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958-2015." *Scientific Data* 5:1–12.

Adao, Rodrigo, Costas Arkolakis, and Federico Esposito. 2018. "Trade, Agglomeration Effects, and Labor Markets: Theory and Evidence." In *2018 Meeting Papers from Society for Economic Dynamics.*

Allen, Treb, and Costas Arkolakis. 2014. "Trade and the Topology of the Spatial Economy." *The Quarterly Journal of Economics,* no. 2002: 1085–1139. arXiv: `9809069v1 [arXiv:gr-qc]`.

Anderson, James E, and Eric van Wincoop. 2004. "Trade Costs." *Journal of Economic Literature* 42 (3): 691–751. arXiv: `arXiv:1011.1669v3`.

Antweiler, Werner, Brian R Copeland, and Scott Taylor. 2001. "Is Free Trade Good for the Environnement." *American Economic Review* 91 (4): 807–908. arXiv: `arXiv:1011.1669v3`.

Au, Chun-Chung, and J. Vernon Henderson. 2006a. "Are Chinese Cities Too Small?" *Review of Economic Studies* 73 (3): 549–576.

———. 2006b. "How migration restrictions limit agglomeration and productivity in China." *Journal of Development Economics* 80 (2): 350–388.

Aunan, Kristin, Mette Halskov Hansen, and Shuxiao Wang. 2018. "Introduction: Air Pollution in China." *China Quarterly* 234 (December): 279–298.

Balboni, Clare. 2016. "Living on the Edge: Infrastructure Investments and the Persistence of Coastal Cities." In *Papers presented to a CEP International Economics Workshop.* London: London School of Economics.

Baum-Snow, Nathaniel, L. Brandt, J. V. Henderson, M. A. Turner, and Q. Zhang. 2017. "Road, Railroads, and Decentralization of Chinese Cities." *Review of Economics and Statistics* 99 (3): 435–448.

Baum-Snow, Nathaniel, Loren Brandt, Vernon Henderson, Matthew Turner, and Qinghua Zhang. 2015. "Transport Infrastructure, Urban Growth and Market Access in China." In *ERSA conference papers.* European Regional Science Association.

Baum-Snow, Nathaniel, J. Vernon Henderson, Matthew A. Turner, Qinghua Zhang, and Loren Brandt. 2018. "Does investment in national highways help or hurt hinterland city growth?" *Journal of Urban Economics* 000 (April): 1–19.

Bernard, Andrew B., Jonathan Eaton, J. Bradford Jensen, and Samuel Kortum. 2003. "Plants and productivity in international trade." *American Economic Review* 93 (4): 1268–1290.

Bryan, Gharad, and Melanie Morten. 2019. "The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia." *Journal of Political Economy* 127 (5): 2229–2268.

Caliendo, Lorenzo, and Fernando Parro. 2015. "Estimates of the trade and welfare effects of NAFTA." *Review of Economic Studies* 82 (1): 1–44.

Caliendo, Lorenzo, Fernando Parro, Esteban Rossi-Hansberg, and Pierre Daniel Sarte. 2018. "The impact of regional and sectoral productivity changes on the U.S. economy." *Review of Economic Studies* 85 (4): 2042–2096.

Chen, Shuai, Paulina Oliva, and Peng Zhang. 2017. "The Effect of Air Pollution on Migration: Evidence from China." *NBER Working Paper Series* 24036.

Chen, Yuyu, Ginger Zhe Jin, Naresh Kumar, and Guang Shi. 2013. "GAMING IN AIR POLLUTION DATA? LESSONS FROM CHINA." *NBER Working Paper Series* 18729.

Combes, Pierre Philippe, Sylvie Démurger, Shi Li, and Jianguo Wang. 2019. "Unequal migration and urbanisation gains in China." *Journal of Development Economics* January:1–17.

Copeland, Brian R., and M. Scott Taylor. 1994. "North-South Trade and the Environment." *The Quaterly Journal of Economics* 109 (3): 755–787.

———. 2004. "Trade, Growth and the Environment." *Journal of Economic Literature* 42 (1): 7–71.

Dekle, Robert, Jonathan Eaton, and Samuel Kortum. 2008. "Global rebalancing with gravity: Measuring the burden of adjustment." *IMF Staff Papers* 55 (3): 511–540. arXiv: `arXiv:1011.1669v3`.

Desmet, Klaus, and Esteban Rossi-hansberg. 2015. "On the spatial economic impact of global warming." *Journal of Urban Economics* 88:16–37.

Donaldson, Dave, and Richard Hornbeck. 2016. "Railroads and American Economic Growth: A "Market Access" Approach." *The Quarterly Journal of Economics* 131 (2): 799–858.

Donkelaar, Aaron van, Randall V. Martin, Michael Brauer, N. Christina Hsu, Ralph A. Kahn, Robert C. Levy, Alexei Lyapustin, Andrew M. Sayer, and David M. Winker. 2016. "Global Estimates of Fine Particulate Matter using a Combined Geophysical-Statistical Method with Information from Satellites, Models, and Monitors." *Environmental Science & Technology* 50 (7): 3762–3772.

Eaton, Jonathan, and Samuel Kortum. 2002. "Technology, Geography, and Trade." *Econometrica* 70 (5): 1741–1779.

Faber, Benjamin, and Cecile Gaubert. 2019. “Tourism and economic development: Evidence from Mexico’s coastline.” *American Economic Review* 109 (6): 2245–2293.

Fajgelbaum, Pablo, and Cecile Gaubert. 2019. “Optimal Spatial Policies, Geography and Sorting.” *NBER Working Paper Series* 24632.

Fajgelbaum, Pablo D., Eduardo Morales, Juan Carlos Suárez Serrato, and Owen Zidar. 2019. “State Taxes and Spatial Misallocation.” *Review of Economic Studies* 86 (1): 333–376.

Freeman, Richard, Wenquan Liang, Ran Song, and Christopher Timmins. 2017. “Willingness to Pay for Clean Air in China.” *NBER Working Paper Series* 24157.

Gervais, Antoine, and J. Bradford Jensen. 2019. “The tradability of services: Geographic concentration and trade costs.” *Journal of International Economics* 118:331–350.

Grossman, Gene M., and Alan B. Krueger. 1995. “Economic Growth and the Environment.” *The Quarterly Journal of Economics* 110 (2): 353–377.

He, Jiaxiu, Haoming Liu, and Alberto Salvo. 2019. “Severe air pollution and labor productivity: Evidence from industrial towns in China.” *American Economic Journal: Applied Economics* 11 (1): 173–201.

Head, Keith, and Thierry Mayer. 2004. “The empirics of agglomeration and trade.” In *Handbook of Regional and Urban Economics, Volume 4,* edited by J. Vernon Henderson and Jacques-François Thisse, 4:2609–2669. 04. Elsevier B.V.

———. 2014. “Gravity Equations: Workhorse, Toolkit, and Cookbook.” In *Handbook of Regional and Urban Economics 4.*

Hubbard, Timothy P. 2014. “Trade and transboundary pollution: quantifying the effects of trade liberalization on CO2 emissions.” *Applied Economics* 46 (5): 483–502.

Ito, Koichiro, and Shuang Zhang. 2016. "Willingness to Pay for Clean Air:Evidence from Air Purifier Markets in China." *NBER Working Paper Series* 22367.

Jin, Yana, Henrik Andersson, and Shiqiu Zhang. 2016. "Air pollution control policies in China: A retrospective and prospects." *International Journal of Environmental Research and Public Health* 13 (12).

Karagulian, Federico, Claudio A. Belis, Carlos Francisco C. Dora, Annette M. Prüss-Ustün, Sophie Bonjour, Heather Adair-Rohani, and Markus Amann. 2015. "Contributions to cities' ambient particulate matter (PM): A systematic review of local source contributions at global level." *Atmospheric Environment* 120:475–483.

Landrigan, Philip J., Richard Fuller, Nereus J.R. Acosta, Olusoji Adeyi, Robert Arnold, Niladri Basu, Abdoulaye Bibi Baldé, et al. 2017. "The Lancet Commission on pollution and health." *The Lancet* 6736 (17).

Li, Meng, Huan Liu, Guannan Geng, Chaopeng Hong, Fei Liu, Yu Song, Dan Tong, et al. 2017. "Anthropogenic emission inventories in China: A review." *National Science Review* 4 (6): 834–866.

Liu, Jun, Denise L. Mauzerall, Qi Chen, Qiang Zhang, Yu Song, Wei Peng, Zbigniew Klimont, et al. 2016. "Air pollutant emissions from Chinese households: A major and underappreciated ambient pollution source." *Proceedings of the National Academy of Sciences of the United States of America* 113 (28): 7756–7761.

Moretti, Enrico. 2013. "Real Wage Inequality." *American Economic Journal: Applied Economics* 5, no. 1 (January): 65–103.

Poncet, Sandra. 2003. "Measuring Chinese domestic and international integration." *China Economic Review* 14:1–21.

Poncet, Sandra. 2005. “A Fragmented China : Measure and Determinants of Chinese Domestic Market Disintegration.” *Review of International Economics* 13 (3): 409–430.

Porter, M. E., and C. van der Linde. 1995. “Toward a New Conception of the Environment-Competitiveness Relationship.” *Journal of Economic Perspectives* 9 (4): 97–118.

Redding, Stephen J. 2016. “Goods trade, factor mobility and welfare.” *Journal of International Economics* 101:148–167.

Redding, Stephen J., and Esteban Rossi-Hansberg. 2017. “Quantitative Spatial Economics.” *Annual Review of Economics* 9 (1): 21–58.

Roback, J. 1982. “Wages, Rents, and the Quality of Life.” *Journal of Political Economy* 90 (6): 1257–1278.

Rooij, Benjamin van. 2006. “Implementation of Chinese Environmental Law: Regular Enforcement and Political Campaigns.” *Development and Change* 37 (1): 57–74.

Rooij, Benjamin van, and Carlos Wing-hung Lo. 2010. “Fragile Convergence: Understanding Variation in the Enforcement of China’s Industrial Pollution Law.” *LAW & POLICY* 32 (1): 14–37.

Rosen, S. 1979. “Wage-Based Indexes of Urban Quality of Life.” In *Current Issues in Urban Economics,* edited by P. Mieszkowski and M. Straszheim. Baltimore: Johns Hopkins University Press.

Shapiro, Joseph S., and Reed Walker. 2018. “Why is pollution from us manufacturing declining? the roles of environmental regulation, productivity, and trade.” *American Economic Review* 108 (12): 3814–3854.

Song, Yang. 2014. “What should economists know about the current Chinese hukou system?” *China Economic Review* 29:200–212.

Stoerk, Thomas. 2017. “Compliance, Efficiency, and Instrument Choice: Evidence from Air Pollution Control.” PhD diss.

Sun, Xiaowei, Shuiyuan Cheng, Jianbing Li, and Wei Wen. 2017. “An integrated air quality model and optimization model for regional economic and environmental development: A case study of Tangshan, China.” *Aerosol and Air Quality Research* 17 (6): 1492–1509.

Tombe, By Trevor, and Xiaodong Zhu. 2019. “Trade, Migration, and Productivity: A Quantitative Analysis of China.” *Americal Economic Review* 109 (5): 1843–1872.

Wang, Alex L. 2013. “The Search for Sustainable Legitimacy: Environmental Law and Bureaucracy in China.” *Harvard Environmental Law Review* 37:365–440. arXiv: `0608246v3 [arXiv:physics]`.

Wu, Jing, Yongsheng Deng, Jun Huang, Randall Morck, and Bernard Yeung. 2013. “Incentives and outcomes: China’s Environmental Policy.” *NBER Working Paper* 18754. arXiv: `arXiv:1011.1669v3`.

Yang, Yang. 2018. “Transport Infrastructure, City Productivity Growth and Sectoral Reallocation:” *IMF Working Papers* 276.

Zheng, Siqi, Jing Cao, and Matthew E. Kahn. 2011. “China’s Rising Demand for "Green Cities": Evidence from Cross-City Real Estate Price Hedonics.” *NBER Working Paper* 16992.

Zheng, Siqi, Yuming Fu, and Hongyu Liu. 2009. “Demand for Urban Quality of Living in China: Evolution in Compensating Land-Rent and Wage-Rate Differentials.” *Journal of Real Estate Finance and Economics* 38 (3): 194–213.

Zheng, Siqi, and Matthew E Kahn. 2013. "Understanding China's Urban Pollution Dynamics." *Journal of Economic Literature* 51 (3): 731–772.

Zheng, Siqi, Matthew E Kahn, and Hongyu Liu. 2010. "Towards a system of open cities in China: Home prices, FDI flows and air quality in 35 major cities." *Regional Science and Urban Economics* 40 (1): 1–10.

Zheng, Siqi, Matthew E Kahn, Weizeng Sun, and Danglun Luo. 2014. "Incentives for China's urban mayors to mitigate pollution externalities: The role of the central government and public environmentalism." *Regional Science and Urban Economics* 47:61–71.

Zivin, Joshua Graff, and Matthew Neidell. 2018. "Air Pollution's Hidden Impact." *Science* 359 (6371): 39–40.

Abstruct (in Japanese)

要約

本稿では、生産・消費活動に伴い発生する大気汚染を明示的に内生化した空間均衡モデルを構築した。本モデルには、異なるタイプの労働者（熟練労働者と未熟練労働者）を導入し、大気汚染に対して異なる選好を持つ両者が国内を移住できると仮定した場合の、地域的な環境政策の効果について考察した。2010 年時点での中国のデータに対してモデルのパラメータを較正（キャリブレーション）してシミュレーションを行ったところ、地域的に厳格な環境規制がその地域への「向心力（centripetal force）」として働き、労働者や生産活動を当該地域に引き付け、同時に当該地域及び国全体の汚染排出を削減しうる場合があることが分かった。この結果は、地域的な環境規制を「遠心力（centrifugal force）」と見る従来の考え方とは異なるもので、生産要素（労働力）の移動などを明示的に導入したことで得られたものである。続いて、中国全体で 10 パーセントの工業大気汚染排出を減らすために、削減責任を地域的にどのように割り当てるべきかを考察した。その結果は、少数の豊かな地域に削減責任を集中させる方が、より平等に責任配分をするよりも厚生面および経済生産面で優れたパフォーマンスを上げ得ることが分かった。

キーワード： 中国、大気汚染、国内移民、空間均衡モデル、環境規制

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