Market vs. Planning: Emission Abatement under Incomplete Information and with Local Externalities*

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To achieve a pre-determined target of emission abatement, one can adopt a planning approach, i.e., to carefully distribute and enforce non-tradable permits onto emitters, or use a market approach, i.e., to allow them to trade the permits with each other. We compare the welfare implications of the two approaches under incomplete information about the abatement cost, and with local externalities of such abatement, which may incur, for example, via changes in emissions of other substances. We show that market can address incomplete information but not heterogeneous local externalities; the opposite is true for planning. Therefore, the policy choice depends on the relative significance of the informational and externality problems. Applying the theoretical results to China's abatement of carbon emissions, we show that while a national carbon market can achieve a slightly better welfare outcome than a carefully designed national abatement plan, it will be substantially outperformed by a hybrid scheme, in which planning is applied to regions with the least incomplete information, while the rest are sorted into a limited number of subnational carbon markets by their local externalities of abatement.

Keywords: Emission market, cap-and-trade, carbon abatement, climate change, environmental pollution, economic coordination

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I. Introduction

There are two general categories of policies to achieve a pre-determined target of emission abatement. The first is the use of a market for tradable emission permits, which, by itself, does not involve any centralized processing of information, i.e., planning. The second requires the policymaker to do so, which includes, for example, carefully allocating emission allowances to different emitters, setting certain emission standards, and taxing emissions or subsidizing abatement at specific rates. Thus arise the key questions for policymaking: what are the relative advantages and shortcomings of "market" and "planning," under what conditions should we apply which, and how should we combine them if needed and feasible?

Naturally, the answers to these questions depend on the specific technological, economic, social, political, and ethical background or issues that concern the policymaker. Among them, two concerns are particularly common and important, not only in abatement of undesirable emissions, but also in environmental regulations generally. First, policymakers often understand that they have incomplete information about the cost of abatement, i.e., they do not know about the real cost of abatement as much as the local or private emitters do (e.g., Weitzman 1974). Second, abating emissions of one substance, such as carbon dioxide, often brings down emissions of other substances, such as various air pollutants, which may have significant local externality implications (e.g., IPCC 2007; Burtraw et al. 2003; West et al. 2013; Karlsson, Alfredsson, and Westling 2020).

In this paper, we analyze theoretically the trade-off between the two approaches – "market" vs. "planning" – in abating emissions when these and only these two concerns are present, and then illustrate the theoretical implications in a real-world example. In particular, we focus on a general context in which the policy designer needs to achieve a pre-determined collective target of abatement and compare the welfare implications between a simple Cap-and-Trade scheme (with an exogenous cap) and a carefully specified plan that distributes and enforces non-tradable abatement targets onto individual emitters.[1] We show that, compared to the planning approach, the market approach is good at solving the problem of incomplete information, while having difficulty addressing the problem brought by heterogeneous local externalities of abatement. Therefore, as the policymaker tries to achieve a pre-determined collective target of abatement more efficiently, market will help her more if and only if the concern of incomplete information is more serious than the concern of local externalities. We further show that the relative significance of the two concerns can be characterized by a simple sufficient statistic, and we can approximate the expected welfare loss under market, planning, or any given combination of them across different emitters by an easy-to-compute formula.

We illustrate our theoretical implications in the context of China's effort to reduce carbon emissions. We focus on this context mainly for three reasons. First, China is the biggest emitter of carbon dioxide (Crippa et al. 2020; United Nations Environment Programme 2021), and the Chinese government has set up ambitious goals to reduce carbon emissions in the coming decades.[2] Our illustration would thus have immediate implications for the design and implementation of abatement policies in one of the most important climate policy contexts now in the world. Second, typical in China, where the general discussion about "market vs. planning" has always been alive, abatement planning and carbon markets are also in hot debate. The planning approach has long been rooted since the era of the planned economy and is widely used in environmental regulation (e.g., Xu 2011; Greenstone et al. 2021), whereas a national carbon market that covers only the power-generation sector has eventually been established since 2021, only after a decade of

[1] When incomplete information is present, other policy instruments that belong to the "planning" category, such as setting proper rates for emission taxes or abatement subsidies, or assigning heterogeneous trading ratios in emission trading, may not guarantee to achieve a pre-determined collective target. Our focus here can help one understand the theoretical origins of the welfare implications involved in these more complicated policy options or contexts.

[2] In 2020, President Xi Jinping pledged to reduce carbon emissions in China and promised to achieve carbon neutrality by 2060. This resolution came as a surprise to researchers and policymakers worldwide, as the policy objective is very challenging, especially considering that the country's carbon emissions are still rising (United Nations Environment Programme 2021).

regional pilots (Zhang et al. 2014).[3] Finally, both the informational and externality problems are especially salient in the Chinese context. Given the experience with the planned economy, Chinese policymakers understand the consequences of having incomplete information overlooked (Huang et al. 2017; Xu 2011). Meanwhile, the country sees substantial inter-regional heterogeneity in population density, income, and environmental quality (Greenstone et al. 2021; United Nations Development Programme 2019), so the local externality implications of carbon abatement can be highly heterogeneous across regions.

About incomplete information of the cost of carbon abatement, we first estimate the curves of the marginal abatement cost of carbon emissions for 30 Chinese provinces, respectively, using data on CO_2 emissions, production inputs (capital, labor, and energy use), and outputs (industrial output and GDP) from 2000 to 2017. Then, for each province, we analyze the predicted errors of the estimation. Since a central policy designer can at least learn about the marginal abatement cost of the province as accurately as we do, the variance of our predicted errors yields an upper bound for the incompleteness of information that the central policy designer may have about the marginal abatement cost of the province. Measured by this upper bound, we find that the degree of incomplete information is generally greater in provinces with poorer governance records and more complex industrial structures.

About local externalities of carbon abatement, we focus on the impacts of carbon abatement on air pollution and their consequences on health and the economy. We first document that carbon emissions affect local air pollution across the 30 Chinese provinces from 2011 to 2017, and then monetize local pollution externalities based on existing literature. The size of the local externality depends on the carbon–pollution relationship, the impacts of pollution on local economic and health outcomes, and the population size in each locality. Our calculation shows that there exists substantial heterogeneity in local

[3] China's current carbon market applies a Tradable Performance Standard (TPS) instrument that targets emission intensity (e.g., Goulder et al. 2022), rather than total emissions. We will discuss in detail why we focus on the standard Cap-and-Trade-type market rather than the TPS-type market in Section III.

externalities associated with carbon emissions across different regions. In particular, in provinces with larger populations, such as Henan and Sichuan, the local externalities tend to be more significant.

Combining the two sets of results above, we apply the sufficient statistic from our theoretical framework and compare the relative significance of incomplete information and heterogenous local externalities. It turns out that the welfare loss caused by failing to address incomplete information under a national abatement plan in China would be slightly greater than the welfare loss caused by failing to address heterogeneous local externalities under a national carbon market. The market approach is thus more efficient than the planning approach in achieving a pre-determined target of carbon abatement in China.

This is not to say that a national carbon market will achieve the best possible outcome in social welfare. Guided by our theoretical results, we further discuss two ways to improve. The first is the first-best solution, which is to combine the national carbon market with locality-specific carbon taxes or abatement subsidies. The intuition is that the market will address the informational problem, while the taxes or subsidies will internalize local externalities. That said, due to various constraints that will be discussed in Section VI, this first-best option may face difficulties and take too long to implement in China. Hence, we consider the second alternative: a hybrid scheme that combines subnational carbon markets with a subnational abatement plan: we first allocate some targets and enforce them onto a group of regions about which the central policy designer would have relatively complete information, and then distribute the rest of the collective target to one or multiple separate carbon markets that the rest regions are sorted into by their marginal local externalities of carbon abatement. Based on the formula from our theoretical analysis and the estimates of incomplete information and local externalities from our empirical exercise, we show that, when China tries to reduce carbon emissions, carefully designed hybrid schemes, which combine a subnational abatement plan with a limited number of subnational segmented carbon markets, can achieve substantially better welfare outcomes than a national carbon market and a national abatement plan.

The paper contributes to several strands of literature. On the theoretical side, it is well understood that trading of emission permits has an advantage in achieving cost-effectiveness given incomplete information about the abatement cost (Dales 1968; Weitzman 1974; Goulder 2013; Tietenberg 1980). At the same time, the literature has also recognized the difficulty for such a system to account for heterogenous local externalities, which often arise from heterogeneous local damages of emissions, and policy augmentations, such as heterogenous trading ratios, have been proposed (Farrow et al. 2005; Henry, Muller, and Mendelsohn 2011; Klaassen, Førsund, and Amann 1994; Kuwayama and Brozović 2013; Montgomery 1972; Muller and Mendelsohn 2009; Tietenberg 1980, 1995).

That said, the up-front trade-off between the two concerns is under-analyzed. An earlier thread of literature touches upon the trade-off when comparing various emission policies when the total amount of abatement is endogenous, so some centralized processing of information, i.e., planning, is always involved in these policies (e.g., Krysiak and Schweitzer 2010; Mendelsohn 1986; Williams 2002, 2007; Yates 2002; Yates et al. 2013). More recently, Jacobsen et al. (2020) show that the welfare consequence of unaccounted local externalities depends on their heterogeneity, but they do not focus on incomplete information about the abatement cost; Holland and Yates (2015) and Fowlie and Muller (2019) analyze how incomplete information about the abatement cost complicates the differentiated policy solutions to heterogenous local externalities, rather than the trade-off itself. We analyze this trade-off when an exogenous collective target of abatement is given. This setting is important to analyze, not only because it fits to the real-world policy situations,[4] but also because it allows us to characterize the main trade-off between the market approach and the planning approach in one integrated framework, to show that this trade-off hinges on the relative significance of the information problem and

[4] For example, the EU plans to achieve carbon neutrality by 2050 and the overall number of emission allowances in the EU ETS will decline by 2.2% per year between 2021 and 2030. China sets an ambitious target of achieving carbon neutrality by 2060, which implies the country needs to reduce more than 11 billion tons of carbon emissions within 30 years.

the externality problem, and importantly, to derive a sufficient statistic for the optimal policy choice.

On the empirical side, although China's national carbon market has become the world's largest one based on emissions it covers, given that it is still young, the impacts of carbon trading in China are under-researched. In the literature, Goulder et al. (2022) compare China's Tradable Performance Standard (TPS) instrument with the classic Cap-and-Trade scheme, not focusing on incomplete information and local externalities. A handful of recent studies estimate the impacts of China's regional pilots of carbon trading on firms' innovation, carbon emissions, and economic performances (e.g., Almond and Zhang 2021; Cui et al. 2021), while little is known about its local welfare implications.

We contribute to this line of literature by highlighting that carbon trading will change local air quality and incur additional health costs, which are often under-considered but key to understanding the full consequences of carbon trading, and we show that a hybrid scheme of subnational carbon markets and planning can help alleviate the problem. In this sense, we link the booming literature on the costs and benefits of environmental policies in China (e.g., a recent survey by Greenstone et al. 2021) to the discussion on the distributional, often unintended consequences of environmental and climate policies in more general contexts (e.g., Banzhaf, Ma, and Timmins 2019; Bento 2013; Conte, Desmet, and Rossi-Hansberg 2022; Hsiang, Oliva, and Walker 2019; Jensen et al. 2015; Krusell and Smith 2022; Schmalensee and Stavins 2013).

At a more conceptual level, one fundamental question in economics is to compare economic coordination by market versus planning (Arrow 1951; Debreu 1951; Hayek 1945; Lange 1942; von Mises 1935). A fruitful area following this tradition is pioneered by Weitzman (1974), analyzing planning by quantity versus price control (with applications primarily in environmental economics); the most recent contributions to this area include Mideksa and Weitzman (2019) and Karp and Traeger (2018). Contributing to the general topic of means of economic coordination, we compare the welfare consequences of the market approach, the planning approach and their combinations, while considering two of the most general issues in economic coordination, i.e., incomplete information and externalities of economic activities. Our analysis proposes a simple way to evaluate the relative significance of the two issues and suggests the possibility of welfare improvement by a combination of market and planning, thus linking us to the literature on combining the market and planning approaches in economic and organizational reforms (e.g., Lau, Qian, and Roland 2000; Roland 2000; Che and Facchini 2007; Cowgill et al. 2022). Our illustration shows the relevance of our results to one of the most pressing battlefields for the future of life on this planet, i.e., China's reduction of its carbon emissions.

The rest of this paper is as follows. Section II presents the theoretical framework and results. Section III overviews China's carbon policy background and discusses the data. Section IV estimates the marginal abatement costs of carbon emissions in different provinces and the incomplete information about them. Section V estimates the local pollution externalities caused by carbon emissions. Section VI compares the relative significance of incomplete information and heterogenous local externalities across different Chinese provinces, discusses the welfare implications of a national carbon market and a national abatement plan, and shows how alternative policies can help improve social welfare. Section VII concludes.

II. Theoretical Framework

1. Setting

Consider $N \geq 2$ regions, each of which is denoted by $i = 1, \ldots, N$ and has one profit-maximizing firm. Assume that the firms are immobile. We can thus denote the region and its firm by the same i and use "region" and "firm" interchangeably hereafter. Besides the firms, we assume that there is a policy designer who must achieve an exogenous target $Q > 0$ of total abatement of emissions among all the firms.

Cost of abatement. On the technologies, we assume that if firm i abates $q_i \geq 0$ units of emission from the business as usual scenario, the marginal cost of abatement will be $c_i(q_i) + \theta_i$, where $c'_i(q_i) > 0$, i.e., the marginal cost is strictly increasing in abatement;

θ_i is a random variable with $\mathbf{E}[\theta_i] = 0$, $\mathbf{E}[\theta_i^2] = \sigma_i^2$, and all θ_i s are mutually independent.

Incomplete information. We assume that there is incomplete information about the abatement cost: firm i knows the realization of θ_i, whereas the policy designer knows only its distribution *ex-ante*. This is to say, θ_i, which carries the incomplete information in our model, is defined as any component in the marginal cost of abatement that, from the policy designer's perspective, is not captured by her best estimate of the marginal cost, $c_i(q_i)$.

Local externality of abatement. Besides the abatement cost, we assume that the abatement q_i will generate a local externality, positive or negative, to the region. We assume that the marginal local externality is $x_i(q_i)$, where $x'_i(q_i) \leq 0$, i.e., the marginal local externality is weakly decreasing in abatement.

Externality, firms vs. policy designer. The local externality $x_i(q_i)$ is an externality in the sense that we assume that firm i does not take it into consideration in its decisions; the externality is a local one in the sense that we assume that the policy designer does take it into consideration in her decisions.

Policy designer's objective. The question at hand is, when achieving the abatement target, how the policy designer could minimize *ex-ante* the expectation of the total abatement cost net of the local externalities across all the regions. The total abatement Q may well have global externality implications, but they are not a concern here because Q is exogenous.

Policy options in focus. We will first establish a first-best solution for the policy designer as a theoretical benchmark. After that, we will examine two suboptimal policy options:

- Planning: the policy designer allocates targets to the firms/regions and enforces their fulfillment.

- Market: the policy designer issues targets to the firms/regions; then, the firms/regions trade the targets in a market as price takers; after trading, the firms/regions fulfill their targets at hand.

The examination will help us analyze the welfare implication of a third option, which combines market with planning:

- Hybrid scheme: the N firms are divided into one "plan" group and A separate "market" groups; given the division, the policy designer first allocates targets across the $A+1$ groups, and then has either planning or the market played out within each group.

2. *Analysis*

2.1 First-best Solution

We start our analysis by characterizing the *ex-post* social-optimal allocation of abatement, with which all abatement costs are known, and all local externalities are accounted for. The program for such an allocation is thus

$$\min_{q_1,\ldots,q_N} \quad \sum_{i=1}^{N}\left(\int_0^{q_i}\big(c_i(q)+\theta_i-x_i(q)\big)\,dq\right), \quad \text{s.t.} \quad q_i \geq 0, \quad \sum_{i=1}^{N} q_i = Q. \tag{1}$$

Assuming interior solution, the first-order condition is

$$c_i(q_i^*)+\theta_i-x_i(q_i^*) = c_j\big(q_j^*\big)+\theta_j-x_j\big(q_j^*\big) \equiv p^* \text{ for any } i,j=1,\ldots,N, \tag{2}$$

where $q_1^*,\ldots,q_N^*$ denote the *ex-post* social-optimal allocation of abatement targets and p^* denotes the implied shadow price of targets.

Can the policy designer create a mechanism *ex-ante* to achieve the *ex-post* social-optimal allocation?

Proposition 1. *Assuming interior solution, the policy designer can achieve the ex-post social-optimal allocation by ex-ante incorporating the market with a subsidy scheme* $x_i(q_i)$ *for each firm* i*'s each marginal abatement at* q_i. *Approximating* $x'_i(q_i) \approx 0$ *and denoting* $x_i(q_i) \approx x_i$, *the subsidy scheme can be approximated by a firm-specific subsidy* x_i *for each unit of abatement.*

The proof is in Appendix A. The intuition of Proposition 1 is that the subsidies fully internalize the local externalities of abatement into the firms' consideration, whereas the market allows the firms to work out the most cost-effective allocation of abatement among themselves, given their knowledge of their own net costs of abatement.

With the first-best solution as the theoretical benchmark at hand, we now proceed to analyze the welfare consequences under planning and market.

2.2 Planning

We first analyze planning. Under this scheme, the policy designer is to choose the allocation of targets $\{\bar{q}_i\}_1^N$ by the following program:

$$\min_{\bar{q}_1,\ldots,\bar{q}_N} \mathbf{E}\left[\sum_{i=1}^{N}\left(\int_0^{\bar{q}_i}\big(c_i(q)+\theta_i-x_i(q)\big)\,dq\right)\right], \quad \text{s.t.} \quad \bar{q}_i \geq 0, \quad \sum_{i=1}^{N}\bar{q}_i = Q. \tag{3}$$

Lemma 1. *Under planning, assuming interior solution, the ex-ante optimal allocation of abatement targets* $\{\bar{q}_i\}_1^N$ *satisfies the first-order condition*

$$c_i(\bar{q}_i) - x_i(\bar{q}_i) = c_j(\bar{q}_j) - x_j(\bar{q}_j) \equiv \bar{p} \textit{ for any } i,j = 1,\ldots,N,$$

where $\bar{p}$ *denotes the implied shadow price.*

The proof is in Appendix B. The main step is to recognize that the incomplete information in our setting only shifts the marginal costs of abatement and does not change their slopes. Therefore, given each firm's abatement, the expected welfare implication of the shift will be the same as the welfare implication of the expected shift, whereas the expected shift is zero. The policy designer will thus decide the ex-ante optimal allocation of targets as if the incomplete information did not exist.

By comparing the first-order condition in Lemma 1 with that for the ex-post social optimal allocation, i.e., Equation (2), we see that the ex-ante optimal allocation of targets has taken the local externalities of abatement into account, but it is ex-ante to and thus independent of the realization of $\theta_1,\ldots,\theta_N$. We can thus expect the incomplete information about the marginal cost of abatement to induce some welfare loss under planning.

We can further illustrate the intuition in Figure 1. In the figure, for simplicity, we assume $N = 2$, so the full allocation of targets requires $q_1 + q_2 = Q$. The ex-post social-optimal allocation of targets (q_1^*, q_2^*) is achieved where the true social marginal costs $c_i(q_i) + \theta_i - x_i(q_i)$ intersect with each other. Under planning, the policy designer only knows the distribution of θ_i and, by Lemma 1, will choose the ex-ante optimal allocation of targets $(\bar{q}_1, \bar{q}_2)$, where the estimated social marginal costs $c_i(q_i) - x_i(q_i)$ intersect with each other. For illustration, we assume $\theta_1 = 0$. The shaded area is thus the ex-post welfare loss.

In Figure 1, we observe that, first, the ex-post welfare loss depends on the differences between the true and estimated social marginal cost curves, whenever incomplete information exists, i.e., the realization of θ_2 in this illustration. Therefore, the more significant the incomplete information is, i.e., the greater the variances of θ_2 in this illustration, the greater the expected welfare loss. Second, the welfare loss depends on the slopes of these marginal cost curves: in this illustration, given the realization of θ_2, the steeper these curves, the smaller the difference θ_2 can make between the ex-post social-optimal and ex-ante optimal allocations of targets, and the smaller the welfare loss. This is consistent with the insight of Weitzman (1974) that the welfare consequence of a mis-specified price incentive is decreasing in the slope of the marginal cost.

With the graphical intuition at hand, we now formally analyze the expected welfare loss under planning, which is defined by

$$\Delta W^{Plan} \equiv \mathbf{E}\left[\sum_{i=1}^{N}\left(\int_0^{q_i^*}\big(x_i(q) - \theta_i - c_i(q)\big)\,dq - \int_0^{\bar{q}_i}\big(x_i(q) - \theta_i - c_i(q)\big)\,dq\right)\right]. \tag{4}$$

Lemma 2. *Assuming interior solution, approximating* $c''_i(q_i) \approx 0$ *and* $x'_i(q_i) \approx 0$*, and denoting* $c'_i(q_i) \approx c'_i$*, the expected welfare loss under planning can be approximated by*

$$\Delta W^{Plan} \approx \frac{1}{2} \cdot S \cdot V_\theta,$$

where

$$V_\theta \equiv \sum_{i=1}^{N} w_i\,(1-w_i)\sigma_i^2, \qquad w_i \equiv \frac{\frac{1}{c'_i}}{\sum_{i=1}^{N}\frac{1}{c'_i}}, \qquad S \equiv \sum_{i=1}^{N}\frac{1}{c'_i}.$$

The proof is in Appendix C, involving a series of linear approximations near the ex-post social-optimal and ex-ante optimal allocations of targets. The graphical intuition in Figure 2 turns out robust: the expected welfare loss is approximately a triangle, so there is a $1/2$ in the formula; the size of the triangle is increasing in the significance of the incomplete information of the marginal costs of abatement, measured by V_θ, a weighted sum of the variances of all θ_is; it is also decreasing in the slopes of the marginal cost curves, which is measured negatively by S, the sum of the inverses of the slopes.

2.3 Market

About the market approach, we first characterize the market-equilibrium allocation of abatement under the system:

Lemma 3. *With a market, assuming interior solution, the market-equilibrium allocation of abatement* $\{q_i^m\}_1^N$ *satisfies the first-order condition*

$$c_i(q_i^m) + \theta_i = c_j\left(q_j^m\right) + \theta_j = p^m \ \textit{for any}\ \ i, j = 1, \dots, N,$$

where p^m *denotes the equilibrium price in the market.*

The proof is in Appendix D. The main step is to recognize the law of one price in the market of abatements, following the first-order condition for each firm, who is taking the equilibrium price in the market of targets as given.

By comparing the first-order condition in Lemma 3 with that for the ex-post social optimal allocation, i.e., Equation (2), we can see that the market-equilibrium allocation of targets under the market has taken the realization of $\theta_1, \dots, \theta_N$ into account, but it misses the local externalities of abatement, so we should expect some welfare loss under the market.

We can further illustrate the intuition in Figure 2. The same as in Figure 1, we assume $N = 2$, so the full allocation of targets requires $q_1 + q_2 = Q$, and the social-optimal allocation of targets (q_1^*, q_2^*) is achieved where the social marginal costs $c_i(q_i) + \theta_i - x_i(q_i)$ intersect with each other. Under the market, by Lemma 3, the market-equilibrium allocation of targets (q_1^m, q_2^m) is achieved where the private marginal costs $c_i(q_i) + \theta_i$ intersect with each other, without having the local externalities considered. The shaded area is thus the welfare loss.

In Figure 2, we observe that, first, the welfare loss depends on the differences in the marginal local externalities between regions: the more equal these unaccounted marginal local externalities, the smaller the welfare loss. Second, similar to Figure 1, the welfare loss depends on the slopes of the marginal cost curves: given the unaccounted marginal local externalities $x_1(q_1)$ and $x_2(q_2)$, the steeper these curves, the smaller the difference $x_1(q_1)$ and $x_2(q_2)$ can make between the social-optimal allocation and the market-equilibrium allocations of targets, and the smaller the welfare loss, which is, again, consistent with Weitzman (1974).

With the graphical intuition at hand, we now formally analyze the expected welfare loss under the market, which is defined by

$$\Delta W^{Market} \equiv \mathbf{E}\left[\sum_{i=1}^{N}\left(\int_0^{q_i^*}\big(x_i(q) - \theta_i - c_i(q)\big)\,dq - \int_0^{q_i^m}\big(x_i(q) - \theta_i - c_i(q)\big)\,dq\right)\right]. \tag{5}$$

Lemma 4. *Assuming interior solution, approximating* $c''_i(q_i) \approx 0$ *and* $x'_i(q_i) \approx 0$, *and denoting* $c'_i(q_i) \approx c'_i$ *and* $x_i(q_i) \approx x_i$, *the expected welfare loss under the market can be approximated by*

$$\Delta W^{Market} \approx \frac{1}{2} \cdot S \cdot D_x,$$

where

$$D_x \equiv \sum_{i=1}^{N}\big(w_i \cdot (x_i - \bar{x})^2\big), \quad \bar{x} \equiv \sum_{i=1}^{N} w_i\, x_i, \quad w_i \equiv \frac{1}{c'_i} \Big/ \sum_{i=1}^{N} \frac{1}{c'_i}, \quad S \equiv \sum_{i=1}^{N} \frac{1}{c'_i}.$$

The proof is in Appendix E, involving a series of linear approximations near the social-optimal allocation and the market-equilibrium allocation of targets. The graphical intuition in Figure 2 holds indeed: the welfare loss is approximately a triangle, so a $1/2$ appears in the formula, too, as in Lemma 2; the size of the triangle is increasing in the heterogeneity in the marginal local externalities of abatement, measured by D_x, a weighted sum of the squared deviations of all x_i s from their weighted average $\bar{x}$; it is also decreasing in the slopes of the marginal cost curves, measured negatively by the same S as in Lemma 2.

It is noteworthy that our theoretical analysis suggests the expected welfare losses under the planning and market approaches are both independent of the exogenous collective target of abatement, Q. This is because under the market, planning, or ex-post social-optimal allocation, the collective target is always fully achieved. Therefore, any misallocation of abatement targets under the planning or market approach comes only from missing either the incomplete information, θ_i, or the marginal local externality, x_i, but is not related to the collective target.

2.4 Market vs. Planning

With the expected welfare losses under both schemes at hand, the expected welfare difference between the two is thus defined by the expression $\Delta W^{Plan} - \Delta W^{Market}$.

Proposition 2. *Assuming interior solution, approximating* $c''_i(q_i) \approx 0$ *and* $x'_i(q_i) \approx 0$*, and denoting* $c'_i(q_i) \approx c'_i$ *and* $x_i(q_i) \approx x_i$*, the expected welfare gain from the market over planning can be approximated by*

$$\Delta W^{Plan} - \Delta W^{Market} \approx \frac{1}{2} \cdot S \cdot (V_\theta - D_x),$$

which is increasing in V_θ*, decreasing in* D_x*, following the sign of* $V_\theta - D_x$*, and proportional to* S*, where*

$$V_\theta \equiv \sum_{i=1}^{N} w_i\,(1 - w_i)\sigma_i^2, \quad D_x \equiv \sum_{i=1}^{N} w_i\,(x_i - \bar{x})^2,$$

$$\bar{x} \equiv \sum_{i=1}^{N} w_i\, x_i, \quad w_i \equiv \frac{1}{c'_i} / \sum_{i=1}^{N} \frac{1}{c'_i}, \quad S \equiv \sum_{i=1}^{N} \frac{1}{c'_i}.$$

Proposition 2 just follows Lemmas 2 and 4. It shows that the policy designer's *ex-ante* choice between the market and planning approaches is about a trade-off between having incomplete information or heterogenous local externalities solved. The market approach addresses the incomplete information problem while missing heterogenous local externalities; the opposite is true for planning. Therefore, *ex-ante*, whether the market approach will be a better policy option depends on the relative significance of incomplete information and heterogeneous local externalities, which, by Lemmas 2 and 4, is determined by comparing V_θ and D_x. Finally, this trade-off will be magnified by flatter slopes of marginal costs of abatement, which is measured by S.

2.5 Hybrid Scheme

Given the trade-off, a natural question to ask is, what is the welfare implication if we combine market with planning, i.e., to apply planning to some firms while assigning the others into one or several separate markets, only after distributing the collective targets among these separate groups?

To answer the question, consider a hybrid scheme, under which the firms are divided into $A+1 \geq 2$ groups. Each group is denoted by $a \in \{0,1,\dots,A\}$, the set of firms in each group is denoted by I^a, and the set of all the firms is denoted by $I \equiv \bigcup_{a=0}^{A} I^a$. Among these groups, Group 0 is under planning, whereas each of the other groups forms a separate market. Given this division, the policy designer is to choose the allocation of targets, $\bar{Q}^0, \dots, \bar{Q}^A$, across the $A+1$ groups, understanding that each of the allocations will be further allocated across the firms in each group by either planning or a market. Mathematically, assuming interior solutions within each of the $A+1$ groups, the program is

$$\min_{\bar{Q}^0,\dots,\bar{Q}^A} \quad \mathbf{E}\left[\sum_{i\in I^0}\left(\int_0^{\bar{q}_i}\big(c_i(q)+\theta_i-x_i(q)\big)\,dq\right)\right] + \sum_{a=1}^{A}\left(\mathbf{E}\left[\sum_{i\in I^a}\left(\int_0^{q_i^m}\big(c_i(q)+\theta_i-x_i(q)\big)\,dq\right)\right]\right),$$

where $\{\bar{q}_i\}_{i\in I^0}$ is the ex-ante social-optimal allocation within the "plan" group and $\{q_i^m\}_{i\in I^a}$, where $a=1,\dots,A$, is the market-equilibrium allocation within each "market" group, subject to a full allocation of targets across all groups, i.e.,

$$Q=\sum_{a=0}^{A}\bar{Q}^a, \quad \bar{Q}^a\geq 0 \text{ for any } a=0,\dots,A,$$

an *ex ante* social-optimal allocation of targets within the "plan" group, i.e.,

$$\sum_{i\in I^0}\bar{q}_i=\bar{Q}^0, \quad c_i(\bar{q}_i)-x_i(\bar{q}_i)=c_j(\bar{q}_j)-x_j(\bar{q}_j)\equiv\bar{p}^0 \text{ for any } i,j\in I^0,$$

and a market-equilibrium allocation of targets within each "market" group $a=1,\dots,A$, i.e.,

$$\sum_{i\in I^a}q_i^m=\bar{Q}^a, \quad c_i(q_i^m)+\theta_i=c_j(q_j^m)+\theta_j\equiv p^{ma} \text{ for any } i,j\in I^a, a=1,\dots,A.$$

The expected welfare loss under the hybrid scheme is thus defined by

$$\Delta W^{Hybrid}\equiv\mathbf{E}\left[\sum_{i\in I^0}\left(\int_0^{q_i^*}\big(x_i(q)-\theta_i-c_i(q)\big)\,dq-\int_0^{\bar{q}_i}\big(x_i(q)-\theta_i-c_i(q)\big)\,dq\right)\right] + \sum_{a=1}^{A}\left(\mathbf{E}\left[\sum_{i\in I^a}\left(\int_0^{q_i^*}\big(x_i(q)-\theta_i-c_i(q)\big)\,dq-\int_0^{q_i^m}\big(x_i(q)-\theta_i-c_i(q)\big)\,dq\right)\right]\right),$$

where $\{\bar{Q}^a\}_{a=0}^A$ solves the policy designer's program, q_i^* still denotes the *ex-post* social-optimal allocation of abatement targets, and p^* denotes the implied shadow price of targets, with

$$c_i(q_i^*)+\theta_i-x_i(q_i^*)=c_j(q_j^*)+\theta_j-x_j(q_j^*)\equiv p^* \text{ for any } i,j\in I.$$

Proposition 3. *Assuming interior solutions, approximating* $c''_i(q_i) \approx 0$ *and* $x'_i(q_i) \approx 0$, *and denoting* $c'_i(q_i) \approx c'_i$ *and* $x_i(q_i) \approx x_i$, *the expected welfare loss under the hybrid scheme can be approximated by*

$$\Delta W^{Hybrid} \approx \frac{S^0}{2} \cdot V_\theta^0 + \sum_{a=1}^{A} \left(\frac{S^a}{2} \cdot D_x^a \right) + \frac{S}{2} \cdot \tilde{V}_\theta,$$

where, for any $i \in I^a$,

$$w_i \equiv \frac{\frac{1}{c'_i}}{\sum_{i \in I} \frac{1}{c'_i}}, \quad \widetilde{w}_i \equiv \frac{\frac{1}{c'_i}}{\sum_{i \in I^a} \frac{1}{c'_i}};$$

for any $a = 0, \dots, A$,

$$S^a \equiv \sum_{i \in I^a} \frac{1}{c'_i}, \quad V_\theta^a \equiv \sum_{i \in I^a} \widetilde{w}_i \, (1 - \widetilde{w}_i)\sigma_i^2, \quad \bar{x}^a \equiv \sum_{i \in I^a} \widetilde{w}_i \, x_i, \quad D_x^a \equiv \sum_{i \in I^a} \widetilde{w}_i \, (x_i - \bar{x}^a)^2;$$

for the whole program,

$$S \equiv \sum_{i \in I} \frac{1}{c'_i}, \quad \tilde{V}_\theta \equiv \sum_{i \in I} w_i \, (\widetilde{w}_i - w_i)\sigma_i^2.$$

We prove Proposition 3 in Appendix F. The intuition turns out to be simple. The formula for the expected welfare loss has three terms. On the one hand, the first two terms replicate Lemmas 2 and 4 but at the group level: they are the expected welfare losses from the $A + 1$ groups supposing that the allocation of targets across groups are ex-post social-optimal.

On the other hand, because of the existence of incomplete information, the policy designer would not be able to reach the ex-post social-optimal allocation of targets across groups. The third term of the formula thus represents the expected welfare loss from this source. Note that this term will become generally greater when there are a greater number of separate "market" groups, because having more separate "market" groups would make the difference between the within-group weight $\widetilde{w}_i$ and the within-program weight w_i greater; this term will vanish to zero only when all the firms are in one group, i.e., when the hybrid scheme degenerates into a national planning scheme or a national market scheme, making $\widetilde{w}_i - w_i = 0$ for any firm i.

3. Implications and Next Steps

Following Proposition 2, the first implication of our analysis is described in Table 1, a rule of thumb for the policy designer when thinking about whether to apply the market approach or the planning approach. The former should be applied when incomplete information about the cost of carbon abatement is more important than the heterogeneity in the marginal local externalities of the abatement among the regions, industries, or firms in focus, while the latter should be applied when the opposite is true.

Table 1 also identifies when further policy analysis would be highly beneficial: it is when the policy designer has relatively incomplete information about the focal regions, industries, or firms, marginal local externalities are highly heterogeneous, and marginal costs of abatement are flat.

As the market approach misses heterogenous local externalities, it is tempting to think that dividing all firms or regions into finely sorted separate markets by their marginal local externalities must be able to improve social welfare. Proposition 3 implies that this logic is flawed: dividing the firms or regions into a greater number of groups involves a greater expected welfare loss in allocating the targets across these groups; at the extreme, if each of the firms or regions is sorted into a market that includes only itself, the whole system will degenerate into a national planning scheme, leaving the concern of incomplete information not addressed at all. Therefore, having many finely sorted, separate markets may not improve social welfare.

With all being said, when choosing from a national emission market, a national abatement plan, and different hybrid schemes, the policy designer should compare the expected welfare losses under these policy options. It is straightforward to compute them. Specifically, one can estimate c_i' and σ_i by estimating the marginal private costs of abatement, and then estimate x_i by estimating the marginal local externalities of abatement. With these estimates at hand, by Lemmas 2, 4, Propositions 2, and 3, one can estimate the expected welfare losses under market, planning, and any hybrid scheme with a given division. We now illustrate this procedure in the context of China's carbon abatement.

III. Background and Data

1. China's Efforts to Reduce Carbon Emissions

Before 2020, China did not set explicit climate or carbon abatement targets. However, policies of planning aiming to improve energy efficiency have long been used in practice. These policies were often incorporated into China's Five-Year Plans, a method of planning economic activities over limited periods that has been used since 1953. Specifically, China started to set an energy efficiency target in its "Eleventh Five Year Plan (2006–2010)" and planned to reduce energy consumption per dollar GDP by 20% within the five years. A major policy initiative during this period was a pilot energy-saving program that required more than 1,000 major energy-consuming enterprises in China to reduce their energy intensity (the "Top 1,000 Enterprises" program). Each enterprise was assigned a specific energy efficiency target. However, because there existed significant production leakages within the large conglomerates, the program was not very successful (Chen et al. 2021). From 2006 to 2010, China's total carbon emissions continued to grow rapidly (Figure 3).

Observing that the "Eleventh Five Year Plan" did not slow down energy consumption, during China's "Twelfth Five-Year Plan (2011–2015)," in addition to setting a national target of improving energy efficiency by 2015, the central government assigned specific target for each province and used these targets for political evaluations.[5] Meanwhile, the government expanded the "Top 1,000 Enterprises" program to the "Top 10,000 Enterprises" program, which targeted more than 10,000 large energy-consuming enterprises that together consumed more than 60% of China's total energy. Further, other

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[5] Tianjin, Shanghai, Jiangsu and Guangdong need to reduce energy intensity by 18% from 2011 to 2015: Beijing, Hebei, Liaoning, and Shandong by 17%; Shanxi, Jilin, Heilongjiang, Anhui, Fujian, Jiangxi, Henan, Hubei, Hunan, Chongqing, Sichuan, and Shanxi by 16%; Inner Mongolia, Guangxi, Guizhou, Yunnan. Gansu, and Ningxia by 15%; Hainan, Tibet, Qinghai, and Xinjiang by 10%.

major energy-consuming sectors, like manufacturing, construction, transportation, agriculture, public utilities, and commercial and residential buildings, were also required to improve their energy efficiency (National Development and Reform Commission 2011). The combination of these policies significantly changed China's carbon emission path. As shown in Figure 3, the growth of China's total carbon emissions and energy consumption immediately slowed down in 2012, and the entire country's energy use has since maintained relatively stable.

More recently, China became interested in using the market approach to reduce energy consumption, with the most important policy being the introduction of carbon trading. In 2011, China started to pilot carbon trading for selected sectors in eight provinces and municipalities, aiming to accumulate experience on how to organize a carbon market and test how carbon trading works.[6] In 2020, President Xi Jinping announced China's ambition to tackle climate change and set the target of achieving carbon neutrality by 2060. Following his announcement, a series of carbon-abatement policy initiatives were proposed, with the most important one being the launching of a national carbon market, i.e., the China Emission Trading System. In 2021, a national carbon market for the power-generation industry was established, accounting for more than 4 billion tons of carbon emissions in China. The Chinese government plans to include more industries in the market in the coming years, soon making it the world's largest carbon market by the total carbon emissions it covers.[7]

It is worth noting that the carbon market currently used in China is not a classic Cap-and-Trade (CAT) scheme, in which total emissions are fixed and different regions/firms

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[6] For more details about the history of China's carbon market, please refer to Cao et al. (2019), Cui et al. (2021), and Zhang, Wang, and Du (2017).

[7] Currently, the largest also the first carbon market is the EU Emission Trading System, which covers more than 10 thousand installations (about 45% of the EU's greenhouse gas emissions) across 31 countries (Andersson 2019; Metcalf 2019; Metcalf and Stock 2020). In the United States, California also introduced a emission trading system on greenhouse gases in 2013, which covered all installations that emitted more than 25,000 m^3 of annual carbon dioxide in any year between 2009–2012 (Hernandez-Cortes and Meng 2020; Meng 2017).

trade carbon allowances. Instead, it is a Tradable Performance Standard (TPS) instrument that targets emission intensity. We choose to focus on the classic CAT-type market in this paper, with an exogenous cap, mainly for three reasons.

First, in theory, both the classic CAT-type market and the TPS instrument share the inefficiency wedge caused by missing local externalities between the marginal cost of carbon abatement and the price of the emissions permit, while the TPS instrument introduces an additional inefficiency wedge between the marginal cost of economic production that uses carbon emissions as an input, for example, electricity generation, and the price of the output (e.g., Fischer 2001, Goulder et al. 2022). It is thus important to first analyze the implication of the former, shared inefficiency wedge.

Second, technically, analyzing the implication of the additional inefficiency wedge under the TPS instrument requires serious modeling of both the production and demand sides of the output market, for example, the electricity market. This task has been done by the major contribution of Goulder et al. (2022).[8] It is thus reasonable for us not to focus on the same task.

Finally, in terms of the relevance of analysis, the TPS instrument is considered "unconventional," whereas the classic CAT-type market is more widely used in other countries (e.g., Goulder et al., 2022). Even in the Chinese context, under the ambitious and urgent agenda to reduce carbon emissions, "[t]he architects of China's [emission trading system] have indicated that it will eventually move from a rate-based system (TPS) to a mass-based system," i.e., a classic CAT-type market (survey by Karplus 2021; also see Ministry of Ecology and Environment 2020; Zhang 2022). Focusing on the classic CAT-type market will thus produce more general implications and be especially relevant in current and future policy debates.

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[8] Goulder et al. (2022) show that, without considering the inefficiency loss caused by missing local externalities, in their benchmark simulation, the abatement cost incurred in the electricity market would be 34% greater under the TPS instrument than under the classic CAT-type market.

While it is well established that carbon trading can help achieve cost-effectiveness in reducing carbon emissions, concerns were also raised in China. First, many criticize that local governments in the pilot regions of the carbon market assigned too many carbon allowances to firms and they were thus unwilling to participate in the carbon trading (Zhang, Wang, and Du, 2017). As a result, the total number of transactions in the pilot carbon markets had been too low to help learn about the marginal cost of abatement in China. Second, there are already many regulations with a flavor of planning on firms' energy use, which further complicate the learning. Finally and importantly, due to significant regional differences in economic structure, population density, income levels, and substantial sectoral/firm-level differences in production technology and abatement costs, there is a general concern that a fully-integrated national carbon market may bring about unintended distributional consequences (Liu et al. 2013). For example, because carbon emissions and air pollution are highly correlated, carbon trading will redistribute air pollution. If regions with higher marginal abatement costs of carbon have larger populations, allowing them to buy carbon permits from regions with lower marginal abatement costs will incur significant health costs via changes in pollution.

2. Data

To illustrate our theoretical results and to explore which policy option China should adopt to reduce carbon emissions, we compile multiple datasets, including provincial-level energy consumption and carbon emissions data, socio-economic data, air pollution data, and meteorological data.

Data on energy consumption and carbon emissions. We collect energy consumption data from China's Energy Statistical Yearbooks and China's Carbon Emission Accounts & Datasets. We have information on the sectoral consumption of primary fossil fuels (e.g., coal, coke, gasoline, natural gas, fuel oil) at the provincial level. We convert each fuel type into standard coal equivariant by calorific value conversion factors (National Bureau of Statistics 2014).

Socio-economic data. We collect provincial-level GDP, labor, capital stock, and energy inputs to estimate the marginal abatement cost of carbon. The first two variables are obtained from the provincial statistical yearbook. The provincial capital stock data are estimated using the perpetual inventory method proposed by Zhang, Wu, and Zhang (2004). Throughout the paper, we adjust all the monetary values to 2015 using China's Consumer Price Index and the exchange rate between CNY and USD (1 USD=6.51 CNY).

Air pollution and meteorological data. We collect air pollution data to understand its relationship with carbon emissions. The pollutant emission data (e.g., SO2, industrial dust, and NOx) are obtained from provincial yearbooks from 2011 to 2017. We also collect the ambient air quality data from station-level air quality monitoring data based on more than 1,600 monitoring stations (Air Quality Index (AQI), PM2.5, PM10, SO2, NO2, O3, and CO) from 2015 to 2017.[9] Because air quality can be affected by weather conditions, we collect meteorological data, including temperature and precipitation, from the Global Historical Climatology Network of the U.S. National Oceanic and Atmospheric Administration. The pollution data and meteorological data are used to estimate the carbon-pollution relationships in different provinces.

IV. Estimating Marginal Abatement Cost Curves and Degrees of Incomplete Information

1. Method

We start by estimating the marginal abatement cost curve (MACC) for each Chinese province and the degree of incomplete information about it. There are three steps. In the first step, we estimate each province's marginal abatement cost (MAC) each year by the Directional Distance Function (DDF) method. We choose the DDF method over alternatives, such as other Distance Functions methods and the Integrated Assessment

[9] Air Quality Index (AQI) is a comprehensive measure of air pollution adopted by the Chinese government. It is constructed by the $PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3, and CO readings. Details about the construction of AQI can be found in Table S1.

Models approaches (e.g., Auffhammer 2018; Kuik, Brander, and Tol 2009), because it is the most widely used method for policy simulations in the Chinese context (e.g., survey by Ma, Hailu, and You, 2019). Heuristically, the MAC is obtained by, first, estimating the production frontier where GDP and CO2 emissions are outputs, and then, by predicting the substitution rate between them on the estimated frontier (Chung, Färe, and Grosskopf 1997; Färe et al. 1993, 2005). Appendix G provides details about the DDF method and summarizes the MAC estimation results.[10]

In the second step, we estimate the amount of carbon abatement for each province from 2011 to 2017. We utilize the policy change in 2011 to construct the counterfactuals. Recall that in 2011 China introduced the "Top 10,000 Enterprises" program, which sharply changed the trend in the nation's carbon emissions. We thus assume that if there were no such policy changes, each province would continue to emit carbon following its pre-2011 GDP-CO2 relationship. Given this assumption, we then predict each province's counterfactual carbon emissions after 2011 and compare them with the actual emissions, getting the amount of carbon abated in each year.

In the third step, for each province, we combine the MAC and abatement estimates after 2011 and use a linear regression to estimate the marginal abatement cost curves (MACC). Linking back to the model, we calculate the Standard Error of the Estimate ($SEE = \sqrt{\sum(y_i - \hat{y})^2\ /(n-2)}$) from each province's regression, which is an estimate of σ_i, where $n = 7$ is the number of years of observations. Supposing that the central government can do at least as well as we do in estimating the marginal abatement cost in each province, our estimate of σ_i can serve as an upper bound of the incompleteness of the central government's information about the provincial marginal abatement cost.

10 Note that the literature on estimating the marginal cost of abating carbon has not been much affected by the "credibility revolution" in empirical economics (Angrist and Pischke 2010), so an obvious critique of the MAC estimation is that it does not exploit "exogenous shocks" for more credible identification.

2. *Results*

Figure 4 illustrates the process of estimating the marginal abatement cost curve using data from Henan province. First, based on the GDP-carbon tradeoff, we estimate the marginal abatement cost using the DDF method each year, as indicated by the dotted dark blue line in Panel A. Then, we calculate the amount of carbon abatement caused by policy change in 2011. The predicted counterfactual emissions are represented by the red line, which follows the pre-2011 trend in carbon emissions. The differences between the predicted carbon emissions and actual carbon emissions are the estimated abated carbon emissions. Finally, we fit the regression line between the two variables and estimate each province's marginal abatement cost curve, which is shown in Panel B of Figure 4.

Figure 5 summarizes the fitted MACCs for 30 Chinese provinces where we have complete data. We observe that the goodness of fit is quite imperfect for certain provinces, such as Liaoning, Jiangxi, and Heilongjiang, implying potential gain from carbon trading among these provinces in solving the informational problem. In Panel A and Panel B of Figure 6, we plot the correlations of the estimate of incomplete information with, respectively, the number of corruption investigations in the province during China's recent anti-corruption campaign (2012–2018), and the province's Herfindahl-Hirschman Index (HHI), which is constructed by sector level employment and indicates negatively the complexity of the industrial structure. These two figures show that the incomplete information tends to be more severe in provinces with more corruption investigations and more complex industrial structures.

In Panel A of Figure 7, we further plot the SEE (estimated σ_i) of each province on the map of China, with a darker color indicating a larger σ_i and greater information asymmetry between the central government and local regions. Based on our model, the relative advantage of introducing a carbon market will be greater if the participating regions are in darker green, holding other factors constant.

V. Estimating Local Externalities of Carbon Abatement

1. Method

Estimating local externalities of carbon abatement involves three steps. First, quantify the association between carbon emissions and air pollution. Second, estimate the health and economic impacts of air pollution for each province. Third, monetize these impacts on a per unit of emission basis for each province.

We first show that carbon emissions are highly correlated with emissions of different air pollutants. In Panel A of Figure S3, we use provincial cross-sectional data and show that provinces that emit large amounts of carbon also emit large amounts of different air pollutants (industry dust, SO2, NOx). In Panel B of Figure S3, we further examine the relationship between carbon emissions and ambient air quality. We observe a similar, albeit nosier pattern that carbon emissions are positively correlated with different ambient air quality measures, as measured by ambient PM2.5, SO2, and NOx concentrations.[11]

Formally, we estimate the relationship between carbon emissions and air pollution using the following equation:

$$\ln(p_{it}) = \gamma \ln(c_{it}) + X_{it} + \theta_i + \delta_t + \varepsilon_{it}, \tag{6}$$

where p_{it} is an air pollution indicator in province i year t, c_{it} is carbon emission in province i year t, X_{it} is a set of weather controls that may affect pollution concentrations, θ_i indicates a set of province fixed effects, and δ_t is a set of year fixed effects, ε_{it} is the error term. The standard errors are clustered at the province level.

Table 2 reports the regression results. There are six ambient air quality measures: Air Quality Index (AQI), PM2.5, PM10, SO2, NO2, CO, and Ozone. We find that carbon emissions are positively associated with all the air pollutants, and the estimated coefficients are all statistically significant at the conventional level. Notably, a 1% increase in carbon

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[11] Air quality data are available in the urban cities only. We average the city-level concentrations of different air pollutants to province level for this analysis.

emissions is associated with a 0.36% increase in PM2.5, which is the primary air pollutant in most Chinese cities. In Table S2, we also summarize the regression results for air pollutant emissions. We find that a 1% increase in carbon emission is associated with a 0.49% increase in industrial dust emissions, a 0.96% increase in SO2 emissions, and a 0.3% increase in NOx emissions.

After obtaining the carbon-pollution relationships, in the second step, we calculate the local external costs caused by changes in air quality.[12] This analysis relies on previous estimates on the impacts of air pollution in China. We focus on four outcomes that are affected by air pollution: mortality costs, morbidity costs, productivity loss, and defensive expenditures. To do so, we borrow estimates from four quasi-experimental studies that have explicitly addressed the endogeneity of air pollution, which include (1) Fan, He, and Zhou (2020)'s research on air pollution and mortality, (2) Barwick et al. (2018)'s research on the morbidity costs of air pollution, (3) Fu, Viard, and Zhang (2021)'s research on air pollution and firm productivity, (4) Ito and Zhang (2020)'s research on defensive expenditure.[13]

In the final step, we monetize the mortality externality using the concept of Value of Statistical Life (VSL). We calculate Chinese people's willingness to pay for each life year following the strategy used in Fan, He, and Zhou (2020), with more details provided in Appendix H. Although carbon emissions are associated with multiple air pollutants, existing studies often focus only on estimating the impacts of one or two specific air pollutants (for example, PM2.5 or PM10).[14] As a result, the impacts of other air pollutants

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[12] For now, we estimate the carbon-pollution relationship using the national data. A better approach is to estimate this relationship separately for each province. We will update the results when more disaggregated data become available to us.

[13] The four studies we cite here focus on changes in short-term pollution exposure and use monthly or yearly data to estimate the pollution impacts. In reality, long-term exposure to air pollution may cause larger health damages (see, for example, Ebenstein et al. (2017)'s research on life expectancy). Therefore, we are likely understating the welfare losses caused by local externality under the market.

[14] For example, Ito and Zhang (2020) quantifies individuals' willingness to pay for removing PM_{10}, but not SO2, NOx, or other pollutants.

(like SO2, NOx, CO, and Ozone) are left out. Our local pollution externality estimate should thus be interpreted as the lower bound of actual local externality.

Specifically, the local monetized pollution externality in province i caused by per unit change in carbon emissions in a specific year are calculated using the following formula:

$$LocalEC_i = pop_{i,2017} * \hat{\gamma}_i * \sum_j \hat{a}_j \tag{7}$$

where pop_i indicates the population in province i in 2017; $\hat{\gamma}_i$ is the estimated change in air pollution per unit change in carbon emissions and we obtain $\hat{\gamma}_i$ by multiplying the pollution-carbon elasticity, i.e., the estimate of γ from Equation (6), by the provincial pollution levels in 2017; $\hat{a}_j$s are the estimated health and economic costs of per unit change in air pollution for outcome j.

2. Results

Our estimates on the local externality of carbon emissions are summarized on the map in Panel B of Figure 7. A darker color indicates a higher marginal local externality of carbon abatement. As Equation 4 suggests, provinces that have large populations tend to have higher marginal local externalities of carbon abatement (such as Sichuan and Henan), and provinces with smaller populations (like Xinjiang, Inner Mongolia, and Ningxia) have lower marginal local externalities of carbon abatement. Based on our model, the relative advantage of planning will be greater when the participating regions have more heterogeneous local externalities, i.e., a greater diversity in their depths of the red color, holding other factors constant.

VI. Welfare Analysis

1. Market vs. Plannning

Figure 8 summarizes the expected welfare losses under the national carbon market and planning. The red bars, ΔW^{Plan}, characterize the welfare losses under planning caused by failing to address incomplete information. The blue bars, ΔW^{Market}, represent the welfare losses under the carbon market caused by failing to address heterogeneous local externalities. Comparing the two expected welfare losses we see that the national carbon market is more efficient in achieving a given collective target of carbon abatement because the expected welfare loss under the market (18.55 billion USD/Year) is smaller than the expected welfare loss under planning (28.65 billion USD/Year).

2. *Ways to Improve*

Given that both approaches have their limitations, can we improve the welfare outcome by alternative policies? The answer is yes. Following the theoretical analysis, we discuss the implications of two potentially welfare-improving strategies: (1) the first-best solution that combines the national carbon market with locality-specific abatement subsidies, and (2) well-designed hybrid schemes that combine a subnational abatement plan with one or multiple subnational carbon markets.

The first-best solution. The first-best solution is simply to apply Proposition 1. To be specific, the local subsidy rate should be equal to the marginal local externality, whose pattern has been captured by Figure 8.

In practice, however, this strategy faces a few significant challenges. First, institutionalizing a new tax/subsidy through the National Congress in China often takes a long time and involves a highly uncertain and complex decision process. According to some of China's carbon market architects' discussions, China's carbon abatement agenda is too urgent to wait, and it will take too long to implement a carbon tax scheme (Zhang, 2022); relatedly, it is also mentioned that even if such tax/subsidy schemes were established, their management costs would be regarded as too high (Zhang 2022). Another concern is about "perceived fairness": if different firms or regions face different levels of taxes/subsidies in a unified national carbon market, it could be criticized as discriminating against certain market participants, while one of the main objectives of China's economic reform in recent decades has been to level the playing field of competition (e.g., Naughton, 2018; Bai et al., 2021; Communist Party of China Central Committee and State Council, 2022). Further, under the firm/region-specific subsidy or tax schemes, local governments could compete with each other by distorting the taxes or subsidies; given the tradition of local protectionism in China, this outcome could be expected (Wedeman, 2003; Bai et al., 2004, 2021; Li and Zhou, 2005; Barwick, Cao, and Li, 2021; Communist Party of China Central Committee and State Council, 2022). In light of all this, applying a national carbon market with region/firm-specific subsidy or tax schemes has not been under much discussion, whereas a national carbon abatement plan, a national carbon market, and combinations of the market and planning approaches are more relevant in practice.

The hybrid schemes. The second option is to combine a subnational abatement plan with subnational carbon markets. Specifically, the policy designer should first assess the degrees of incomplete information in different regions' marginal abatement costs and apply the planning approach only among regions with relatively complete information. For example, the regulators may be more familiar with certain regions than others or have more knowledge about the production technology in certain firms/industries than others. In these cases, planning is preferred as it will lead to a smaller welfare loss in expectation. Then, the policy designer should sort the other regions that she is unfamiliar with into separate subnational carbon markets by their marginal local externalities of abatement.

We illustrate this idea using our estimates in Sections IV and V. We first rank the 30 Chinese provinces by their degrees of incomplete information. For the Top x provinces where incomplete information is of the least concern, we apply planning. For the remaining $30 - x$ provinces with higher degrees of incomplete information, we sort them into one or multiple subnational carbon markets of equal number of provinces by their marginal local externalities. We then estimate the expected total welfare loss of the hybrid scheme by Proposition 3.

The results are plotted in Figure 9. There are two important observations. First, allowing more regions to engage in carbon trading helps address incomplete information, but this is achieved at the cost of missing heterogenous local externalities, and the cost can be especially high when more and more regions are covered by carbon trading. This trade-off is reflected in the observation that the curve for the one-market hybrid schemes is non-monotonic, and the best combination is achieved when ten, neither none nor all, regions are in the market.

Second, given the number of regions in carbon markets, the more finely we sort them into separate markets, the lower the markets' cost caused by missing heterogeneous local externalities, but the less incomplete information the markets can address. Given this trade-off, it is generally not ideal to use only one carbon market or too many markets. As shown in the figure, as long as we have more than 15 provinces in the ETSs, having two markets dominates having only one, three, or four markets.

Quantitatively, it turns out that a hybrid scheme could significantly bring down the welfare loss. For example, when we assign twenty provinces to the subnational abatement plan and the rest ten provinces to one subnational market, the total expected welfare loss is estimated to be around 9.86 billion USD/Year, which is 65.6% lower than the national planning benchmark, and 30.3% lower than the national market benchmark. If we sort all the 30 provinces into a hybrid scheme with one subnational abatement plan and two subnational carbon markets (i.e., the solid orange line in Figure 10), the lowest welfare loss will be achieved when none of the provinces is assigned to the plan and all of them are split into two subnational markets. The corresponding welfare loss will be around 6.78 billion USD/Year, which is respectively 76.33% and 63.44% lower than the national planning case and the national market case.

VII. Conclusion

This paper compares the welfare consequences of "market" with "planning" when achieving a pre-determined collective target of emission abatement, taking into consideration both incomplete information about abatement costs and local externalities of abatement. We show that the comparison depends on the relative significance of the informational problem to the heterogeneity in local externalities, and we derive a simple sufficient statistic for the trade-off, a rule of thumb for the policy choice, and a formula to estimate the expected welfare loss of any hybrid scheme that combines planning with market.

We illustrate the theoretical results by applying them to the debate about China's strategy to reduce carbon emissions. In the empirical context, we find that the welfare losses under both policies are non-negligible, although the welfare loss under the carbon market is still smaller than that under planning. We further discuss alternative policies to improve social welfare, including the combination of a national carbon market with local subsidies of abatement, and hybrid schemes that consist of a subnational abatement plan and a limited number of subnational carbon markets. We show that these alternatives can significantly improve social welfare upon the national planning and market benchmarks, thus worth further exploration.

Our results have important policy implications. First, to mitigate climate change risks, many countries have established, planned, or proposed to establish carbon markets to reduce carbon emissions. However, most policy discussions have focused on the cost-saving side of the carbon markets, and their limitations have not been thoughtfully examined. We highlight the importance of local externalities, both theoretically and empirically, when assessing the welfare consequence of carbon trading, which can help improve the design and operation of the carbon markets.

More importantly, we provide rule-of-thumb policy suggestions for policymakers, informing them of the right tool to use to reduce carbon emissions: (1) for countries with high degrees of incomplete information and relatively homogeneous population size and income levels, the policymakers should consider the carbon market; (2) for countries with relatively complete information in production technology, or large regional heterogeneity in pollution, income, and population, planning may be a better option.

Finally, because carbon emissions and air pollution are highly correlated, policymakers should consider more integrated approaches when designing and implementing climate policies and pollution regulations. In reality, climate and energy policies and pollution regulations are often designed separately.[15] Our analyses show that failing to consider these inter-correlations may create substantial welfare loss.

We conclude by pointing out some caveats in our analysis. First, while we try to be as careful as possible when estimating various parameters in the model using the Chinese data, one should note that the main purpose of the empirical exercise is for illustration. In practice, each step of the parameterization process involves making many assumptions that involve highly subjective decisions. The key decisions we made include: (1) what method should be used to estimate the marginal abatement cost curves and the associated uncertainties, (2) what dimensions/time horizons of local externalities we should focus on, (3) where we should borrow the estimated pollution impacts, (4) how to monetize non-market goods (i.e., human life). Changing the key decisions could produce a different set of results. Second, we do not consider the entry and exit decisions of firms and movements of individuals across different regions, which may have important welfare implications. Third, our framework is static, while dynamic considerations in carbon abatement may be important. Fourth, our empirical analyses use provincial data and focus on how to distribute the collective target from the national to the provincial level. At the more disaggregated levels, such as allocating targets within a province/prefecture/county, we need different sets of data, which will generate different welfare and policy implications. Finally, carbon emissions could have heterogenous local impacts because of the heterogenous local impacts of global warming (e.g., Cruz and Rossi-Hansberg 2021). We overlooked this type of local implications of carbon abatement when calculating the welfare consequences of different policies. We left these more complicated settings for future investigation.

[15] In the Chinese context, for example, the climate policies and pollution regulations have been historically administered two different government agents and there is little synergy in designing and implementing policies between them (Lewis 2013). The climate and energy policies in China were administered the National Development and Reform Commission (NDRC), while the environmental regulations were administered by the Ministry of Environment and Ecology (MEE).

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Tables and Figures

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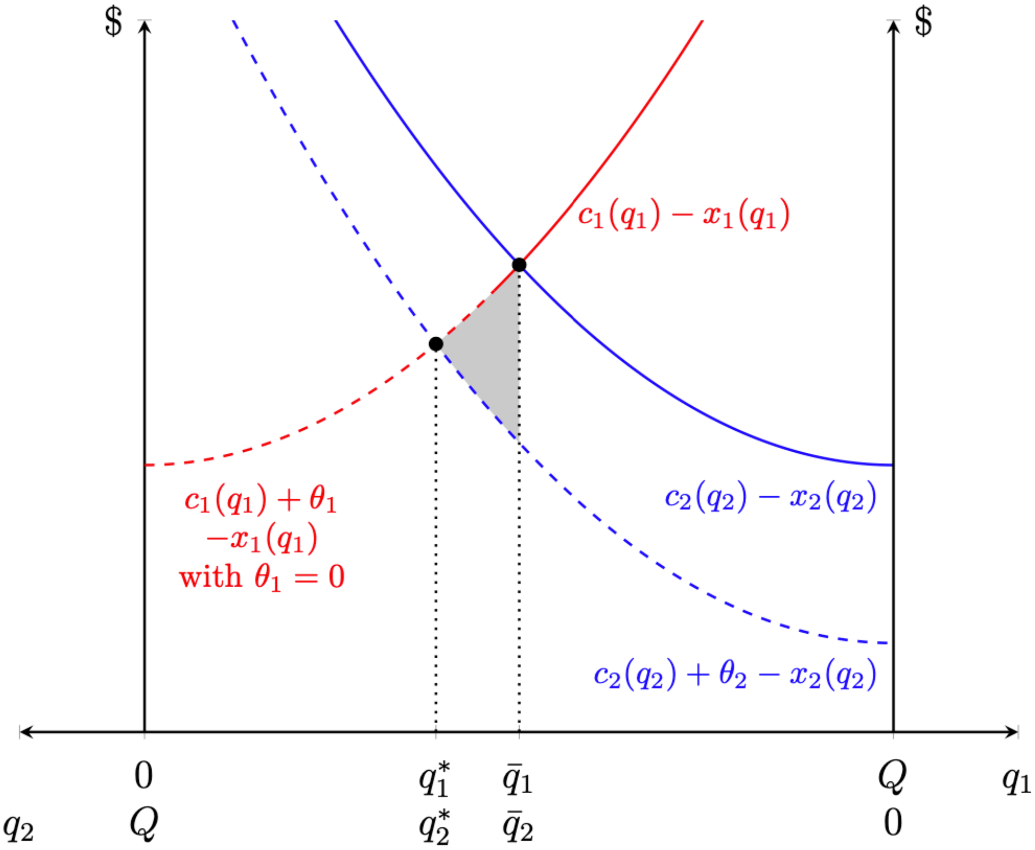


Figure 1. Welfare Implications under Planning

Notes: $N = 2$; $i = 1{,}2$; estimated social marginal cost: $c_i(q_i) - x_i(q_i)$; *ex-ante* optimal allocation of targets: $\bar{q}_i$; true social marginal cost: $c_i(q_i) + \theta_i - x_i(q_i)$; *ex-post* social-optimal allocation of targets: q_i^*. For this illustration, $\theta_1 = 0$. The shaded area represents the *ex-post* welfare loss under planning.

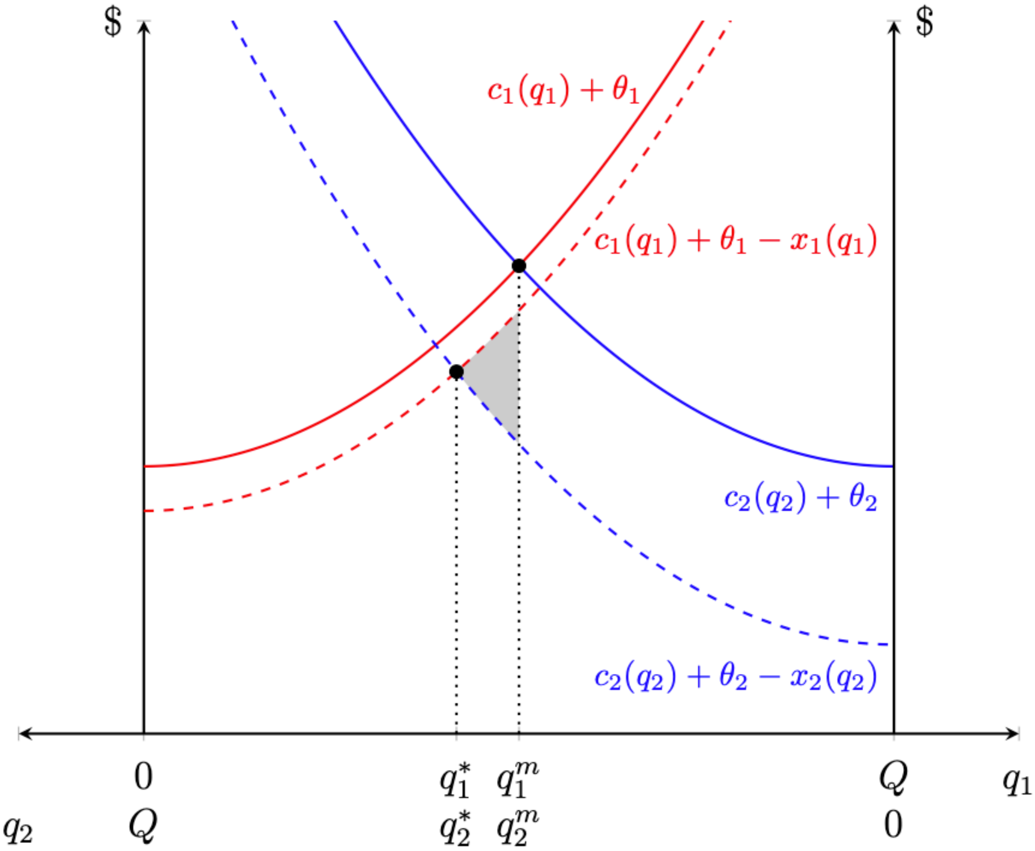


Figure 2. Welfare Implications under Market

Notes: $N = 2$; $i = 1,2$; private marginal cost: $c_i(q_i) + \theta_i$; market-equilibrium allocation of targets: q_i^m; social marginal cost: $c_i(q_i) + \theta_i - x_i(q_i)$; social-optimal allocation of targets: q_i^*. The shaded area represents the welfare loss under the market.

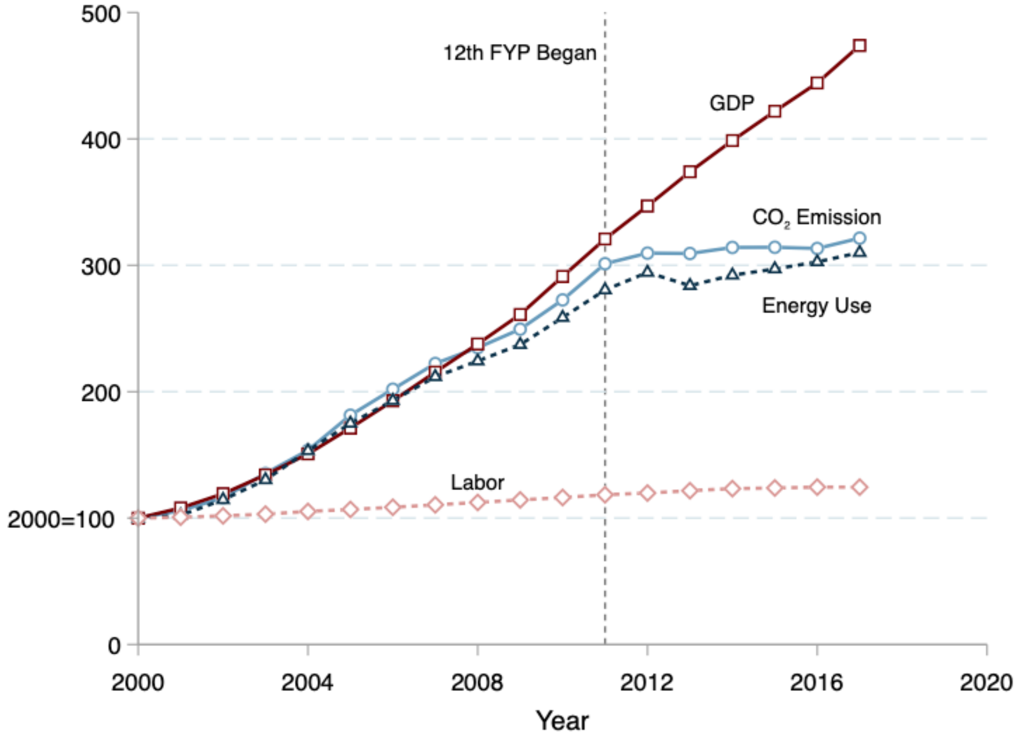


Figure 3. CO_2 Emissions, Energy Use, GDP, and Labor in China

Notes: This figure shows China's GDP, carbon emissions, energy consumption, and labor from 2000 to 2017, with the Year 2000 levels set to be 100. GDP is deflated to the 2015 level. "12th FYP" indicates China's Twelfth Five Year Plan (2011–2015).

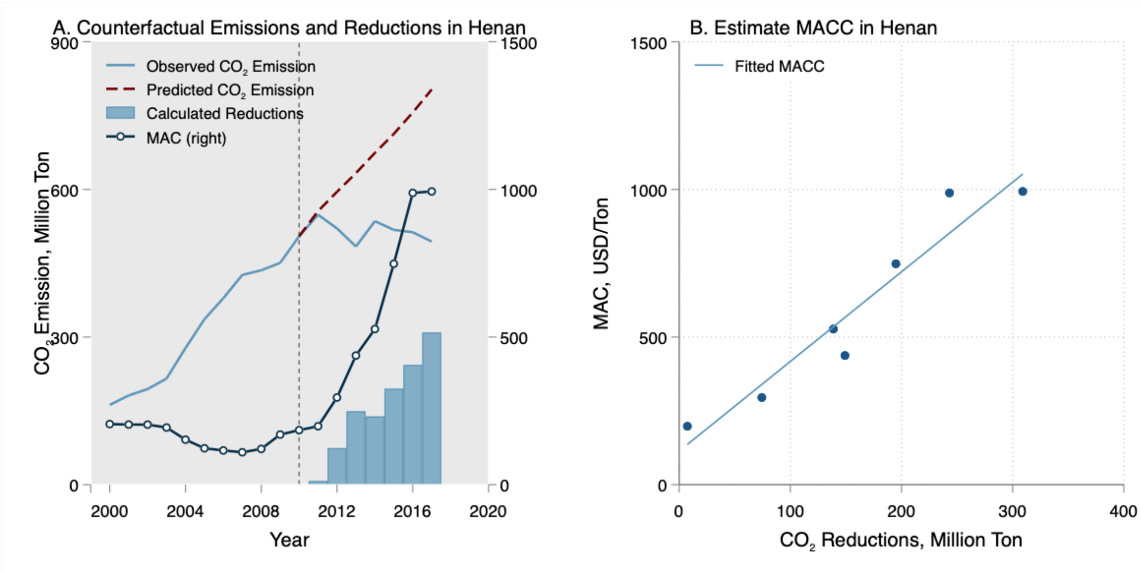


Figure 4. Estimate Marginal Abatement Cost Curve: An Example

Notes: This figure illustrates how to estimate the marginal abatement cost curve using data from Henan Province. First, we estimate the marginal abate cost in each year using the directional output distance function (DDF, the dotted line in Panel A) method. Then we estimate the counter-factual carbon emissions from 2011 to 2017, assuming that carbon emissions would follow the same trend in the absence of energy-efficiency policies implemented in 2011. The differences between the counterfactual carbon emissions and actual emissions are then used to calculate the amount of abatement each year from 2011 to 2017. Then we regress the estimated marginal abatement cost on the estimated carbon reductions in Panel B and obtain the estimated marginal abatement cost curve (MACC).

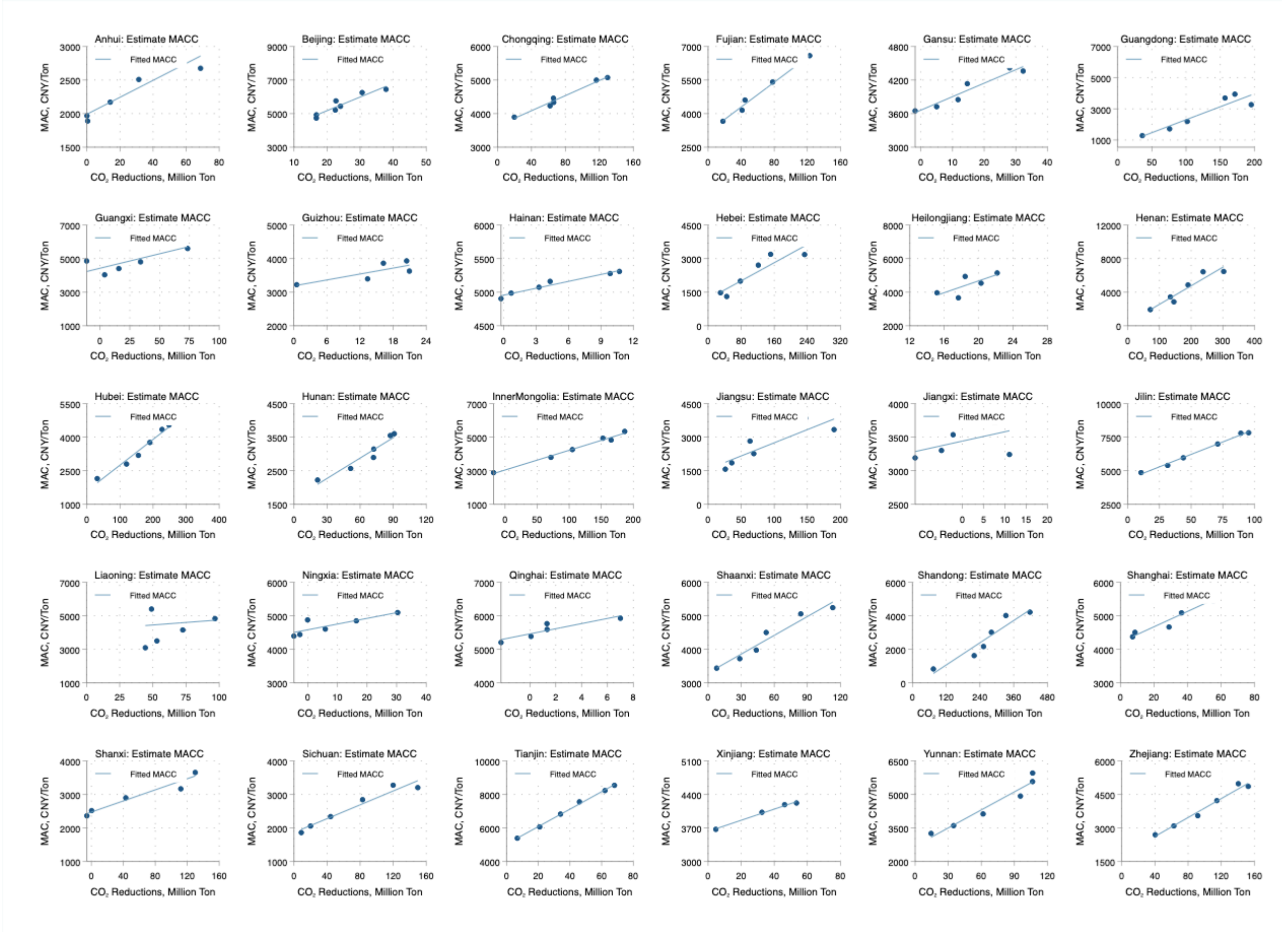
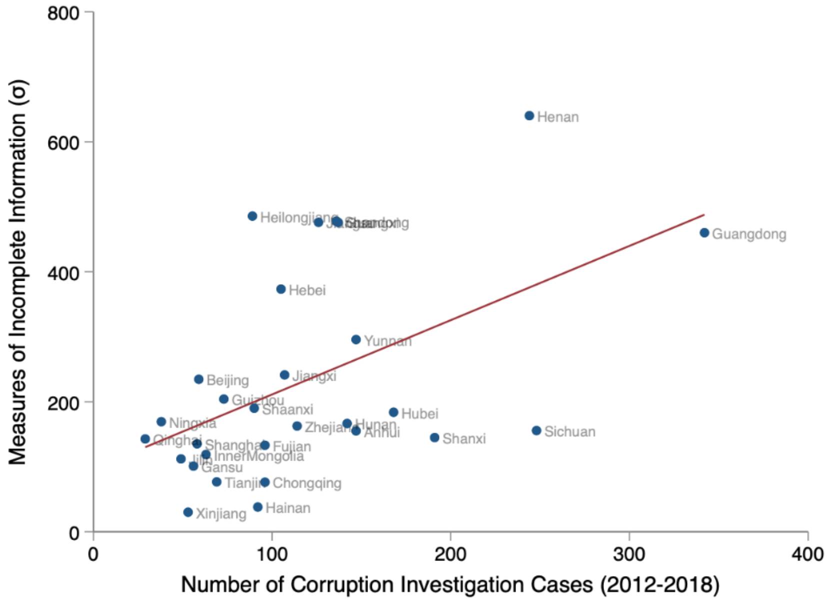


Figure 5. Fitted Marginal Abatement Cost Curves for 30 Provinces

Notes: This figure summarizes the estimated marginal abatement cost curves for 30 provinces in which we have data. The y axis is the estimated marginal abatement cost from the directional output distance function method. The x axis is the estimated carbon abatement.

Panel A. Incomplete Information and the Number of Corruption Investigations



Panel B. Incomplete Information and the Industrial Structure Complexity

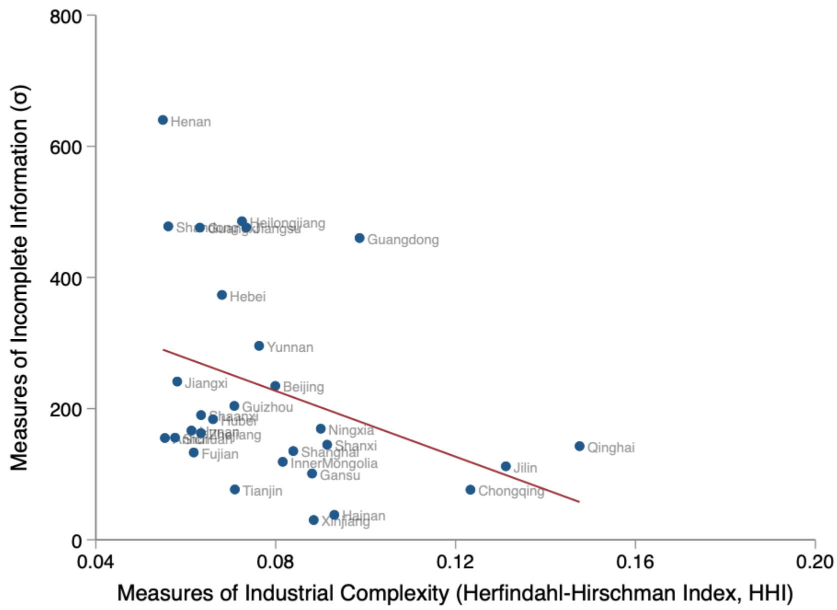
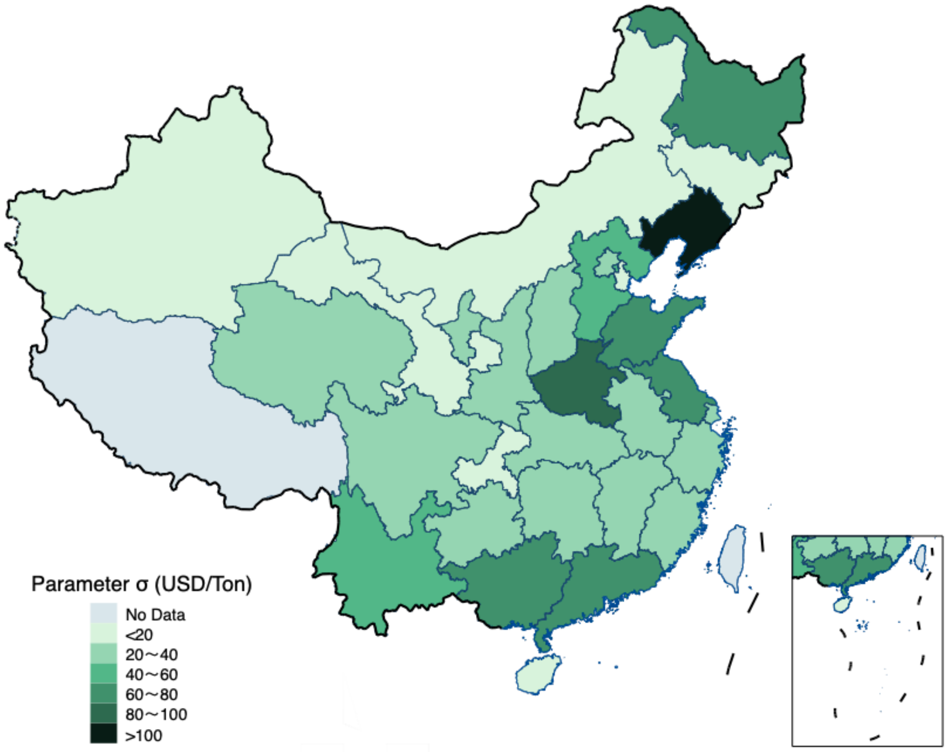


Figure 6. Incomplete Information and Local Characteristics

Notes: Each province's Herfindahl-Hirschman Index, HHI_i, is calculated by $HHI_i = \sum_j \left(\frac{L_{i,j}}{L_i}\right)^2$, where $L_{i,j}$ is the number of employees in sector j in province i from 2012 to 2017, and L_i is the total number of employees in province i during the same period. A higher HHI indicates a less complex industrial structure.

Panel A. Measuring Incomplete Information about MACC in Chinese Provinces



Panel B. Measuring Local Externality of Carbon Abatement in Chinese Provinces

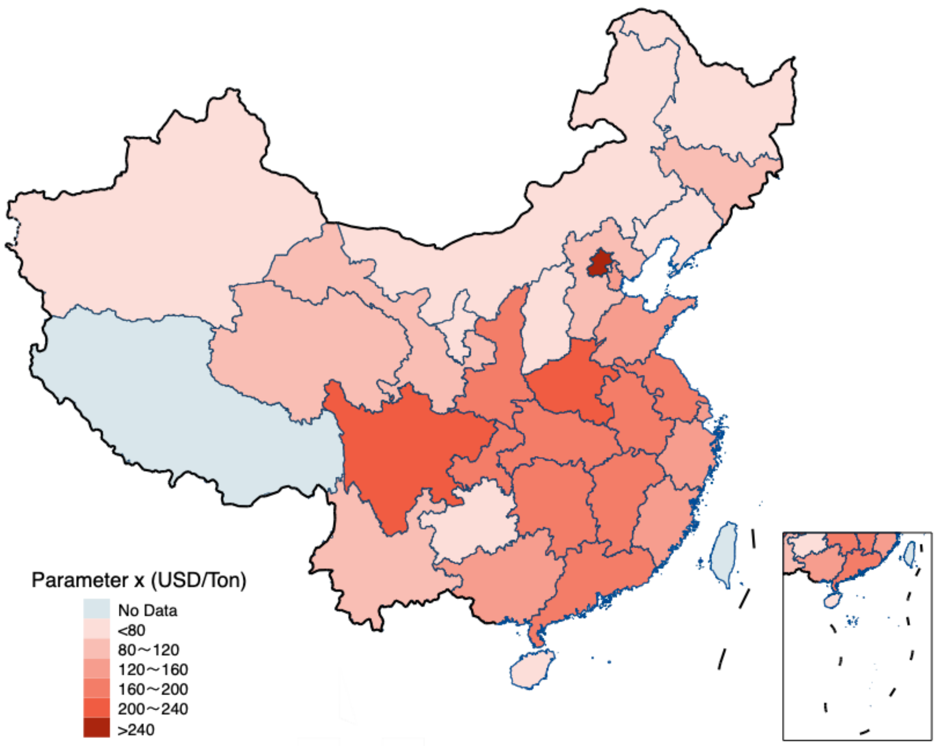


Figure 7. Significance of Information Incompleteness and Local Heterogeneities

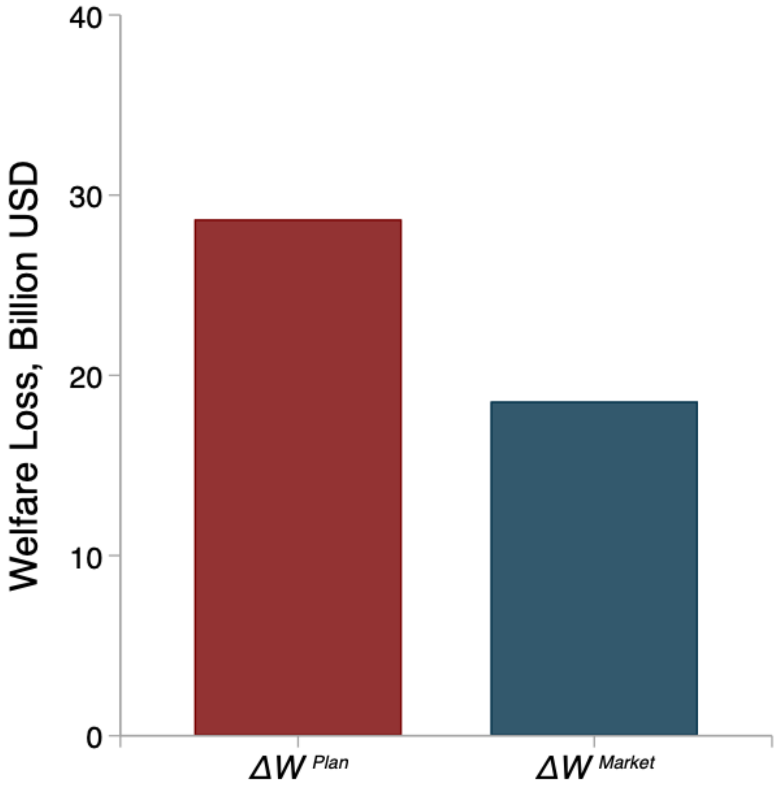


Figure 8. Compare Expected Welfare Losses between Market and Planning

Notes: The red bar, ΔW^{Plan}, is the expected welfare loss under planning caused by failing to address incomplete information. The blue bar, ΔW^{Market}, is the expected welfare loss under the market caused by failing to address heterogeneous local externalities.

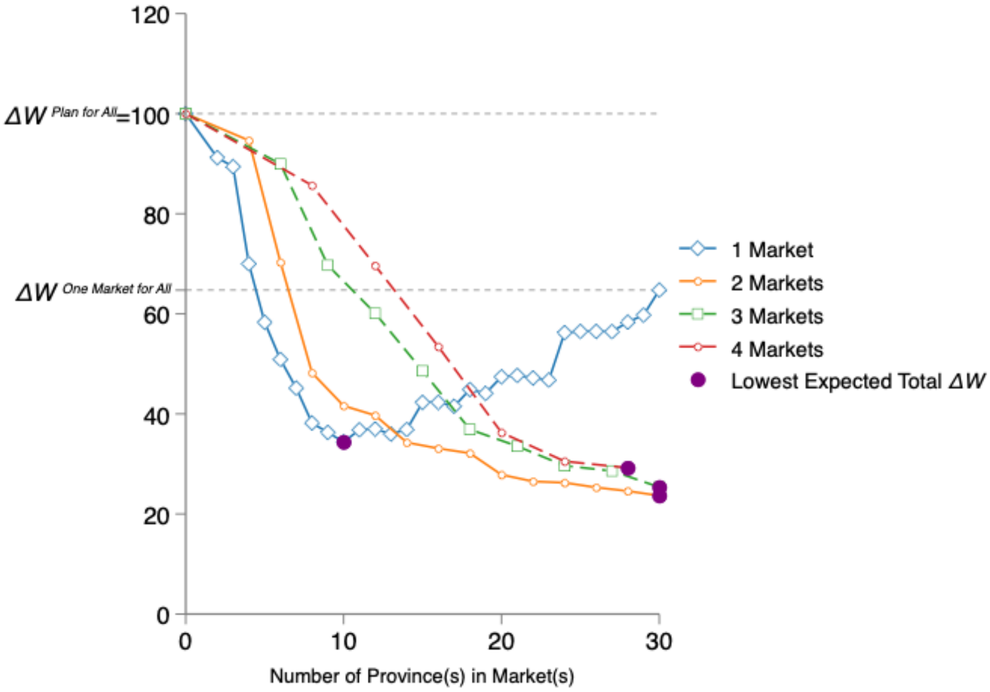


Figure 9. Expected Welfare Losses under Hybrid Schemes

Note: In each hybrid scheme, we first rank the 30 Chinese provinces from high to low based on their degrees of incomplete information. We introduce planning to the top x provinces where incomplete information is of the least concern. We then sort the remaining $30-x$ provinces into one or multiple markets of equal number of provinces by their marginal local externalities of abatement.

Table 1. Rule of Thumb for Policy Choice

	High V_θ, i.e., very incomplete information	Low V_θ, i.e., almost complete information
Low D_x, i.e., homogenous marginal local externalities	Market	Either fine, especially with low S, i.e., steep marginal costs
High D_x, i.e., heterogenous marginal local externalities	Be careful, especially with high S, i.e., flat marginal costs	Plan

Table 2. The Relationship between CO_2 Emissions and Air Pollution

	AQI (log) (1)	$PM_{2.5}$ (log) (2)	PM_{10} (log) (3)	SO_2 (log) (4)	NO_2 (log) (5)	CO (log) (6)	O_3 (log) (7)
CO_2 Emissions	0.33**	0.36**	0.40***	0.44**	0.28*	0.44***	0.28*
(Million Ton, log)	(0.13)	(0.17)	(0.13)	(0.20)	(0.15)	(0.11)	(0.15)
Outcome Mean							
(levels)	74.68	47.86	83.94	21.81	33.02	1.05	76.38
Unit	points	$\mu g/m^3$	$\mu g/m^3$	$\mu g/m^3$	$\mu g/m^3$	mg/m^3	$\mu g/m^3$
R-Squared	0.98	0.97	0.98	0.98	0.98	0.98	0.91
Weather Controls	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	90	90	90	90	90	90	90
Number of Provinces	30	30	30	30	30	30	30

Notes: Each column reports a separate regression on the correlation between CO_2 emissions and air pollution using the provincial data from 2015 to 2017. The independent variable is the logarithm of annual CO_2 emission levels, and the dependent variables are the logarithms of air pollution levels. We collected station-level air quality data and collapse the data to the province-by-year level. The AQI (Air Quality Index) is a comprehensive measure of air pollution used by the Chinese government. It is constructed by different air pollutants listed in Columns (2) to (7). Details about the construction of AQI can be found in Table S1. Standard errors in parentheses are clustered at the province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3. Estimated Costs of Air Pollution in Literatures

	Pollutant	Effect	Literature
Pre-mature Deaths	Air Quality Index (AQI)	10-point increase in AQI can increase the weekly mortality by 3.8%	Fan et al. (2020)
Medical Expenditures	$PM_{2.5}$	10-$\mu g/m^3$ reduction in $PM_{2.5}$ can save 73.45 CNY for each household's annual healthcare cost	Barwick et al. (2018)
Defensive Expenditures	PM_{10}	A household is willing to pay 8.71 CNY annually to remove PM_{10} by 1-$\mu g/m^3$	Ito and Zhang (2020)
Productivity Loss	$PM_{2.5}$	A 1% reduction in $PM_{2.5}$ can increase annually GDP by 0.039%	Fu et al. (2021)

Appendix to "Market vs. Planning: Emission Abatement under Incomplete Information and with Local Externalities"

Appendix A. Proof of Proposition 1

Proof. Denote the initial of abatement targets as $\tilde{q}_i$, where $i = 1, \dots, N$ and $\sum_i^N \tilde{q}_i = Q$, and the equilibrium price in the market of targets as p^m. Firm i is to maximize the profit from target trading, net of its abatement cost, plus the subsidy to receive, by choosing its abatement q_i:

$$\max_{q_i} \quad p^m(q_i - \tilde{q}_i) - \int_0^{q_i} (c_i(q) + \theta_i)\, dq + \int_0^{q_i} x_i\,(q) dq, \quad \text{s.t.} \quad q_i \geq 0.$$

Assuming interior solution, the first-order condition is

$$p^m = c_i(q_i) + \theta_i - x_i(q_i).$$

By the law of one price in the market of targets, we have

$$p^m = c_i(q_i) + \theta_i - x_i(q_i) = c_j\big(q_j\big) + \theta_j - x_j\big(q_j\big) \text{ for any } i, j = 1, \dots, N.$$

Note that this is the same as the first-order condition for the *ex-post* social-optimal allocation of abatement. The proposition then follows.

Appendix B. Proof of Lemma 1

Proof. Observe that as $\bar{q}_i$ is a choice variable and $\mathbf{E}[\theta_i] = 0$, the policy designer's objective function can be reduced into

$$\mathbf{E}\left[\sum_{i=1}^{N}\left(\int_0^{\bar{q}_i}\big(c_i(q) + \theta_i - x_i(q)\big)\,dq\right)\right] = \mathbf{E}\left[\sum_{i=1}^{N}\left(\int_0^{\bar{q}_i}\big(c_i(q) - x_i(q)\big)\,dq\right) + \sum_{t=1}^{N}\theta_i\,\bar{q}_i\right]$$

$$= \sum_{i=1}^{N}\left(\int_0^{\bar{q}_i}\big(c_i(q) - x_i(q)\big)\,dq\right) + \sum_{t=1}^{N}(\mathbf{E}[\theta_i]\cdot\bar{q}_i) = \sum_{i=1}^{N}\left(\int_0^{\bar{q}_i}\big(c_i(q) - x_i(q)\big)\,dq\right).$$

Assuming there is an interior solution, the lemma then follows the first-order condition of the program given the reduced objective function.

Appendix C. Proof of Lemma 2

Proof. By approximating $c''_i(q_i) \approx 0$ and $x''_i(q_i) \approx 0$, we can approximate

$$\begin{aligned}
&\int_0^{\bar{q}_i} \big(x_i(q) - \theta_i - c_i(q)\big)\, dq \\
&\approx \int_0^{q_i^*} \big(x_i(q) - \theta_i - c_i(q)\big)\, dq + \big(x_i(q_i^*) - \theta_i - c_i(q_i^*)\big)(\bar{q}_i - q_i^*) \\
&\qquad + \frac{x'_i(q_i^*) - c'_i(q_i^*)}{2} \cdot (\bar{q}_i - q_i^*)^2.
\end{aligned}$$

Therefore, we can approximate

$$\begin{aligned}
&\int_0^{q_i^*} \big(x_i(q) - \theta_i - c_i(q)\big)\, dq - \int_0^{\bar{q}_i} \big(x_i(q) - \theta_i - c_i(q)\big)\, dq \\
&\approx \int_0^{q_i^*} \big(x_i(q) - \theta_i - c_i(q)\big)\, dq - \int_0^{q_i^*} \big(x_i(q) - \theta_i - c_i(q)\big)\, dq \\
&\qquad - \big(x_i(q_i^*) - \theta_i - c_i(q_i^*)\big)(\bar{q}_i - q_i^*) - \frac{x'_i(q_i^*) - c'_i(q_i^*)}{2} \cdot (\bar{q}_i - q_i^*)^2 \\
&= \big(c_i(q_i^*) + \theta_i - x_i(q_i^*)\big)(\bar{q}_i - q_i^*) + \frac{c'_i(q_i^*) - x'_i(q_i^*)}{2} \cdot (\bar{q}_i - q_i^*)^2.
\end{aligned}$$

By the first-order condition for the ex-post social-optimal allocation of targets $c_i(q_i^*) + \theta_i - x_i(q_i^*) = p^*$, we have

$$\begin{aligned}
&\int_0^{q_i^*} \big(x_i(q) - \theta_i - c_i(q)\big)\, dq - \int_0^{\bar{q}_i} \big(x_i(q) - \theta_i - c_i(q)\big)\, dq \\
&\approx p^* \cdot (\bar{q}_i - q_i^*) + \frac{c'_i(q_i^*) - x'_i(q_i^*)}{2} \cdot (\bar{q}_i - q_i^*)^2.
\end{aligned}$$

Therefore, we have

$$\begin{aligned}
&\sum_{i=1}^{N} \left(\int_0^{q_i^*} \big(x_i(q) - \theta_i - c_i(q)\big)\, dq - \int_0^{\bar{q}_i} \big(x_i(q) - \theta_i - c_i(q)\big)\, dq \right) \\
&\approx \sum_{i=1}^{N} \left(p^* \cdot (\bar{q}_i - q_i^*) + \frac{c'_i(q_i^*) - x'_i(q_i^*)}{2} \cdot (\bar{q}_i - q_i^*)^2 \right) \\
&= p^* \cdot \left(\sum_{i=1}^{N} \bar{q}_i - \sum_{i=1}^{N} q_i^* \right) + \sum_{i=1}^{N} \left(\frac{c'_i(q_i^*) - x'_i(q_i^*)}{2} \cdot (\bar{q}_i - q_i^*)^2 \right).
\end{aligned}$$

Given $\sum_{i=1}^{N} \bar{q}_i = \sum_{i=1}^{N} q_i^* = Q$, we have

$$\sum_{i=1}^{N}\left(\int_0^{q_i^*}\big(x_i(q)-\theta_i-c_i(q)\big)\,dq-\int_0^{\bar{q}_i}\big(x_i(q)-\theta_i-c_i(q)\big)\,dq\right)$$
$$\approx\sum_{i=1}^{N}\left(\frac{c'_i(q_i^*)-x'_i(q_i^*)}{2}\cdot(\bar{q}_i-q_i^*)^2\right).$$

We can thus approximate

$$\begin{aligned}\Delta W^{Plan} &\approx \mathbf{E}\left[\sum_{i=1}^{N}\left(\frac{c'_i(q_i^*)-x'_i(q_i^*)}{2}\cdot(\bar{q}_i-q_i^*)^2\right)\right]\\ &=\frac{1}{2}\cdot\sum_{i=1}^{N}\mathbf{E}\left[\big(c'_i(q_i^*)-x'_i(q_i^*)\big)(\bar{q}_i-q_i^*)^2\right].\end{aligned}$$

Now we can further approximate the expected welfare loss. Note that we have approximated $c''_i(q_i)\approx 0$, so we can denote $c'_i(q_i)\approx c'_i$; by further approximating $x'_i(q_i)\approx 0$, we can denote $x_i(q_i)\approx x_i$. Therefore, we can first approximate

$$c'_i(q_i^*)-x'_i(q_i^*)\approx c'_i.$$

Second, approximate $\bar{q}_i$. By $c'_i(q_i)\approx c'_i$ and $x_i(q_i)\approx x_i$, we can approximate the first-order condition for the ex-ante optimal allocation of targets $c_i(\bar{q}_i)-x_i(\bar{q}_i)=\bar{p}$ by

$$c_i(0)+c'_i\bar{q}_i-x_i\approx\bar{p},\quad \text{i.e.,}\quad \bar{q}_i\approx\frac{\bar{p}+x_i-c_i(0)}{c'_i}.$$

By the full allocation of targets $\sum_{i=1}^{N}\bar{q}_i=Q$, we have

$$\sum_{i=1}^{N}\frac{\bar{p}+x_i-c_i(0)}{c'_i}\approx Q,\quad \text{i.e.,}\quad \bar{p}\approx\frac{Q-\sum_{i=1}^{N}\frac{x_i-c_i(0)}{c'_i}}{\sum_{i=1}^{N}\frac{1}{c'_i}}.$$

Therefore, we can approximate

$$\bar{q}_i\approx\frac{\dfrac{Q-\sum_{i=1}^{N}\frac{x_i-c_i(0)}{c'_i}}{\sum_{i=1}^{N}\frac{1}{c'_i}}+x_i-c_i(0)}{c'_i}.$$

Third, we approximate q_i^*. By $c'_i(q_i)\approx c'_i$ and $x_i(q_i)\approx x_i$, we can approximate the first-order condition for the ex-post social-optimal allocation of targets $c_i(q_i^*)+\theta_i-x_i(q_i^*)=p^*$ by

$$c_i(0)+c'_iq_i^*+\theta_i-x_i\approx p^*,\quad \text{i.e.,}\quad q_i^*\approx\frac{p^*+x_i-c_i(0)-\theta_i}{c'_i}.$$

Given $\sum_{i=1}^{N} q_i^* = Q$, we have

$$\sum_{i=1}^{N} \frac{p^* + x_i - c_i(0) - \theta_i}{c'_i} \approx Q, \quad \text{i.e.,} \quad p^* \approx \frac{Q - \sum_{i=1}^{N} \frac{x_i - c_i(0) - \theta_i}{c'_i}}{\sum_{i=1}^{N} \frac{1}{c'_i}}.$$

Therefore, we can approximate

$$q_i^* \approx \frac{\frac{Q - \sum_{i=1}^{N} \frac{x_i - c_i(0) - \theta_i}{c'_i}}{\sum_{i=1}^{N} \frac{1}{c'_i}} + x_i - c_i(0) - \theta_i}{c'_i}.$$

Taking the second and third approximations, we have

$$(\bar{q}_i - q_i^*)^2$$

$$\approx \left(\frac{\frac{Q - \sum_{i=1}^{N} \frac{x_i - c_i(0)}{c'_i}}{\sum_{i=1}^{N} \frac{1}{c'_i}} + x_i - c_i(0)}{c'_i} - \frac{\frac{Q - \sum_{i=1}^{N} \frac{x_i - c_i(0) - \theta_i}{c'_i}}{\sum_{i=1}^{N} \frac{1}{c'_i}} + x_i - c_i(0) - \theta_i}{c'_i} \right)^2$$

$$= \left(\frac{\theta_i - \frac{\sum_{i=1}^{N} \frac{\theta_i}{c'_i}}{\sum_{i=1}^{N} \frac{1}{c'_i}}}{c'_i} \right)^2 = \frac{\left(\theta_i - \frac{\sum_{i=1}^{N} \frac{\theta_i}{c'_i}}{\sum_{i=1}^{N} \frac{1}{c'_i}} \right)^2}{{c'_i}^2}.$$

Taking it with the first approximation, we can thus approximate

$$
\begin{aligned}
\Delta W^{Plan} \quad &\approx \frac{1}{2}\cdot\sum_{i=1}^{N}\mathbf{E}\left[c'_i\cdot\frac{\left(\theta_i-\frac{\sum_{i=1}^{N}\frac{\theta_i}{c'_i}}{\sum_{i=1}^{N}\frac{1}{c'_i}}\right)^2}{{c'_i}^2}\right]=\frac{1}{2}\cdot\sum_{i=1}^{N}\mathbf{E}\left[\frac{\left(\theta_i-\frac{\sum_{i=1}^{N}\frac{\theta_i}{c'_i}}{\sum_{i=1}^{N}\frac{1}{c'_i}}\right)^2}{c'_i}\right]\\
&=\frac{1}{2}\cdot\sum_{i=1}^{N}\left(\frac{1}{c'_i}\cdot\mathbf{E}\left[\left(\theta_i-\frac{\sum_{i=1}^{N}\frac{\theta_i}{c'_i}}{\sum_{i=1}^{N}\frac{1}{c'_i}}\right)^2\right]\right)\\
&=\frac{1}{2}\cdot\sum_{i=1}^{N}\frac{1}{c'_i}\cdot\sum_{i=1}^{N}\left(\frac{\frac{1}{c'_i}}{\sum_{i=1}^{N}\frac{1}{c'_i}}\cdot\mathbf{E}\left[\left(\theta_i-\sum_{i=1}^{N}\left(\frac{\frac{1}{c'_i}}{\sum_{i=1}^{N}\frac{1}{c'_i}}\cdot\theta_i\right)\right)^2\right]\right)\\
&\equiv\frac{1}{2}\cdot S\cdot\sum_{i=1}^{N}\left(w_i\cdot\mathbf{E}\left[\left(\theta_i-\sum_{i=1}^{N}w_i\,\theta_i\right)^2\right]\right),
\end{aligned}
$$

where

$$
w_i\equiv\frac{\frac{1}{c'_i}}{\sum_{i=1}^{N}\frac{1}{c'_i}},\qquad S\equiv\sum_{i=1}^{N}\frac{1}{c'_i}.
$$

Note that, by the mutual independence among $\theta_1,\dots,\theta_N$ and $\mathbf{E}[\theta_i^2]=\sigma_i^2$, we have

$$
\begin{aligned}
&\mathbf{E}\left[\left(\theta_i-\sum_{i=1}^{N}w_i\,\theta_i\right)^2\right]=\mathbf{E}\left[\left((1-w_i)\theta_i-\sum_{j\neq i}w_j\,\theta_j\right)^2\right]\\
&=(1-w_i)^2\mathbf{E}[\theta_i^2]+\sum_{j\neq i}w_j^2\,\mathbf{E}[\theta_j^2]=(1-w_i)^2\sigma_i^2+\sum_{j\neq i}w_j^2\,\sigma_j^2\\
&=(1-2w_i)\sigma_i^2+\sum_{i=1}^{N}w_i^2\,\sigma_i^2.
\end{aligned}
$$

Therefore, by $\sum_{i=1}^{N}w_i=1$, we have

$$\sum_{i=1}^{N}\left(w_i \cdot \mathbf{E}\left[\left(\theta_i - \sum_{i=1}^{N} w_i\, \theta_i\right)^2\right]\right) = \sum_{i=1}^{N}\left(w_i \cdot \left((1-2w_i)\sigma_i^2 + \sum_{i=1}^{N} w_i^2\, \sigma_i^2\right)\right)$$

$$= \sum_{i=1}^{N}\left(w_i(1-2w_i)\sigma_i^2 + w_i \cdot \sum_{i=1}^{N} w_i^2\, \sigma_i^2\right) = \sum_{i=1}^{N} w_i\,(1-2w_i)\sigma_i^2 + \sum_{i=1}^{N} w_i^2\, \sigma_i^2 \cdot \sum_{i=1}^{N} w_i$$

$$= \sum_{i=1}^{N} w_i\,(1-2w_i)\sigma_i^2 + \sum_{i=1}^{N} w_i^2\, \sigma_i^2 = \sum_{i=1}^{N} w_i\,(1-w_i)\sigma_i^2.$$

We can thus approximate

$$\Delta W^{Plan} \quad \approx \frac{1}{2} \cdot S \cdot \sum_{i=1}^{N} w_i\,(1-w_i)\sigma_i^2 \equiv \frac{1}{2} \cdot S \cdot V_\theta,$$

where

$$w_i \equiv \frac{\frac{1}{c'_i}}{\sum_{i=1}^{N} \frac{1}{c'_i}}, \quad S \equiv \sum_{i=1}^{N} \frac{1}{c'_i}, \quad V_\theta \equiv \sum_{i=1}^{N} w_i\,(1-w_i)\sigma_i^2.$$

Appendix D. Proof of Lemma 3

Proof. Denote the initial allocation of abatement targets as $\tilde{q}_i$, where $i = 1, \dots, N$ and $\sum_{i=1}^{N} \tilde{q}_i = Q$, and the equilibrium price in the market of targets as p^m. Firm i is to maximize the profit from target trading, net of its abatement cost, by choosing its abatement q_i:

$$\max_{q_i} \quad p^m(q_i - \tilde{q}_i) - \int_0^{q_i} (c_i(q) + \theta_i)\, dq, \quad \text{s.t.} \quad q_i \geq 0.$$

Assuming interior solution, the first-order condition is

$$p^m = c_i(q_i^m) + \theta_i,$$

where q_i^m is the market-equilibrium allocation of abatement targets. By the law of one price in the market of targets, we have

$$p^m = c_i(q_i^m) + \theta_i = c_j\left(q_j^m\right) + \theta_j \text{ for any } i, j = 1, \dots, N.$$

Appendix E. Proof of Lemma 4

Proof. First, by approximating $c''_i(q_i) \approx 0$ and $x''_i(q_i) \approx 0$, the first-order condition for the social-optimal allocation of abatement $c_i(q_i^*) + \theta_i - x_i(q_i^*) = p^*$, and total abatement target $\sum_{i=1}^{N} q_i^m = \sum_{i=1}^{N} q_i^* = Q$, similar to the proof of Lemma 2, we can approximate

$$\Delta W^{Market} \approx \frac{1}{2} \cdot \sum_{i=1}^{N} \mathbf{E}\left[\left(c'_i(q_i^*) - x'_i(q_i^*)\right)(q_i^m - q_i^*)^2\right].$$

Now approximate the expected welfare loss further. Similar to the proof of Lemma 2, we can denote $c'_i(q_i) \approx c'_i$; by further approximating $x'_i(q_i) \approx 0$, we can denote $x_i(q_i) \approx x_i$. Therefore, we can first approximate

$$c'_i(q_i^m) - x'_i(q_i^*) \approx c'_i.$$

Second, approximate q_i^m. By $c'_i(q_i) \approx c'_i$, $x_i(q_i) \approx x_i$, the first-order condition for the market-equilibrium allocation of abatement $c_i(q_i^m) + \theta_i = p^m$, the full allocation of targets $\sum_{i=1}^{N} q_i^m = Q$, similar to the proof of Lemma 2, we can approximate

$$q_i^m \approx \frac{\dfrac{Q - \sum_{i=1}^{N} \dfrac{-c_i(0) - \theta_i}{c'_i}}{\sum_{i=1}^{N} \dfrac{1}{c'_i}} - c_i(0) - \theta_i}{c'_i}.$$

Third, approximate q_i^*. As in the proof of Lemma 2, we can approximate

$$q_i^* \approx \frac{\dfrac{Q - \sum_{i=1}^{N} \dfrac{x_i - c_i(0) - \theta_i}{c'_i}}{\sum_{i=1}^{N} \dfrac{1}{c'_i}} + x_i - c_i(0) - \theta_i}{c'_i}.$$

Taking the second and third approximations, we have

$$(q_i^m - q_i^*)^2$$

$$\approx \left(\frac{\frac{Q - \sum_{i=1}^{N} \frac{-c_i(0) - \theta_i}{c'_i}}{\sum_{i=1}^{N} \frac{1}{c'_i}} - c_i(0) - \theta_i}{c'_i} - \frac{\frac{Q - \sum_{i=1}^{N} \frac{x_i - c_i(0) - \theta_i}{c'_i}}{\sum_{i=1}^{N} \frac{1}{c'_i}} + x_i - c_i(0) - \theta_i}{c'_i} \right)^2$$

$$= \left(- \frac{x_i - \frac{\sum_{i=1}^{N} \frac{x_i}{c'_i}}{\sum_{i=1}^{N} \frac{1}{c'_i}}}{c'_i} \right)^2 = \frac{\left(x_i - \frac{\sum_{i=1}^{N} \frac{x_i}{c'_i}}{\sum_{i=1}^{N} \frac{1}{c'_i}} \right)^2}{{c'_i}^2}.$$

Taking it with the first approximation, we can thus approximate

$$\Delta W^{Market} \approx \frac{1}{2} \cdot \sum_{i=1}^{N} \mathbf{E} \left[c'_i \cdot \frac{\left(x_i - \frac{\sum_{i=1}^{N} \frac{x_i}{c'_i}}{\sum_{i=1}^{N} \frac{1}{c'_i}} \right)^2}{{c'_i}^2} \right] = \frac{1}{2} \cdot \sum_{i=1}^{N} \frac{\left(x_i - \frac{\sum_{i=1}^{N} \frac{x_i}{c'_i}}{\sum_{i=1}^{N} \frac{1}{c'_i}} \right)^2}{c'_i}$$

$$= \frac{1}{2} \cdot \sum_{i=1}^{N} \left(\frac{1}{c'_i} \cdot \left(x_i - \frac{\sum_{i=1}^{N} \frac{x_i}{c'_i}}{\sum_{i=1}^{N} \frac{1}{c'_i}} \right)^2 \right)$$

$$= \frac{1}{2} \cdot \sum_{i=1}^{N} \frac{1}{c'_i} \cdot \sum_{i=1}^{N} \left(\frac{\frac{1}{c'_i}}{\sum_{i=1}^{N} \frac{1}{c'_i}} \cdot \left(x_i - \sum_{i=1}^{N} \left(\frac{\frac{1}{c'_i}}{\sum_{i=1}^{N} \frac{1}{c'_i}} \cdot x_i \right) \right)^2 \right)$$

$$\equiv \frac{1}{2} \cdot S \cdot \sum_{i=1}^{N} \left(w_i \cdot \left(x_i - \sum_{i=1}^{N} w_i \, x_i \right)^2 \right) \equiv \frac{1}{2} \cdot S \cdot \sum_{i=1}^{N} (w_i \cdot (x_i - \bar{x})^2)$$

$$\equiv \frac{1}{2} \cdot S \cdot D_x,$$

where

$$w_i \equiv \frac{\frac{1}{c'_i}}{\sum_{i=1}^{N} \frac{1}{c'_i}}, \quad S \equiv \sum_{i=1}^{N} \frac{1}{c'_i}, \quad \bar{x} \equiv \sum_{i=1}^{N} w_i \, x_i, \quad D_x \equiv \sum_{i=1}^{N} (w_i \cdot (x_i - \bar{x})^2).$$

Appendix F. Proof of Proposition 3

Proof. Now approximate the expected welfare loss under the hybrid scheme. From the proofs of Lemmas 2 and 4, for the "planning" group, by $c''_i(q_i) \approx 0$, $x''_i(q_i) \approx 0$, $c_i(q_i^*) + \theta_i - x_i(q_i^*) = p^*$ for any $i \in I^0$, $\bar{Q}^0 = \sum_{i \in I^0} \bar{q}_i$, and $Q^{*0} \equiv \sum_{i \in I^0} q_i^*$, we have

$$\sum_{i \in I^0} \left(\int_0^{q_i^*} \big(x_i(q) - \theta_i - c_i(q)\big)\, dq - \int_0^{\bar{q}_i} \big(x_i(q) - \theta_i - c_i(q)\big)\, dq \right)$$
$$\approx p^* \cdot \big(\bar{Q}^0 - Q^{*0}\big) + \sum_{i \in I^0} \left(\frac{c'_i(q_i^*) - x'_i(q_i^*)}{2} \cdot (\bar{q}_i - q_i^*)^2 \right);$$

for each "market" group $a = 1, \ldots, A$, by $c''_i(q_i) \approx 0$, $x''_i(q_i) \approx 0$, $c_i(q_i^*) + \theta_i - x_i(q_i^*) = p^*$ for any $i \in I^a$, $\bar{Q}^a = \sum_{i \in I^a} q_i^m$, and $Q^{*a} \equiv \sum_{i \in I^a} q_i^*$, we have

$$\sum_{i \in I^a} \left(\int_0^{q_i^*} \big(x_i(q) - \theta_i - c_i(q)\big)\, dq - \int_0^{q_i^m} \big(x_i(q) - \theta_i - c_i(q)\big)\, dq \right)$$
$$\approx p^* \cdot (\bar{Q}^a - Q^{*a}) + \sum_{i \in I^0} \left(\frac{c'_i(q_i^*) - x'_i(q_i^*)}{2} \cdot (q_i^m - q_i^*)^2 \right).$$

Assuming interior solutions, we must have $\sum_{a=0}^{A} \bar{Q}^a = \sum_{a=0}^{A} Q^{*a} = Q$. Therefore, we can approximate

$$\Delta W^{Hybrid} \approx \frac{1}{2} \cdot \Big(\sum_{i \in I^0} \mathbf{E}\left[\big(c'_i(q_i^*) - x'_i(q_i^*)\big)(\bar{q}_i - q_i^*)^2 \right]$$
$$+ \sum_{a=1}^{A} \left(\sum_{i \in I^a} \mathbf{E}\left[\big(c'_i(q_i^*) - x'_i(q_i^*)\big)(q_i^m - q_i^*)^2 \right] \right) \Big).$$

From the proofs of Lemmas 2 and 4, again, for the "planning" group, by $c'_i(q_i) \approx c'_i$, $x_i(q_i) \approx x_i$, $c_i(\bar{q}_i) - x_i(\bar{q}_i) = \bar{p}^0$ and $c_i(q_i^*) + \theta_i - x_i(q_i^*) = p^*$ for any $i \in I^0$, $\bar{Q}^0 = \sum_{i \in I^0} \bar{q}_i$, and $Q^{*0} \equiv \sum_{i \in I^0} q_i^*$, we have

$$(\bar{q}_i - q_i^*)^2$$

$$\approx \left(\frac{\frac{\bar{Q}^0 - \sum_{i\in I^0} \frac{x_i - c_i(0)}{c'_i}}{\sum_{i\in I^0} \frac{1}{c'_i}} + x_i - c_i(0)}{c'_i} - \frac{\frac{Q^{*0} - \sum_{i\in I^0} \frac{x_i - c_i(0) - \theta_i}{c'_i}}{\sum_{i\in I^0} \frac{1}{c'_i}} + x_i - c_i(0) - \theta_i}{c'_i} \right)^2$$

$$= \left(\frac{\theta_i - \frac{\sum_{i\in I^0} \frac{\theta_i}{c'_i}}{\sum_{i\in I^0} \frac{1}{c'_i}} + \frac{\bar{Q}^0 - Q^{*0}}{\sum_{i\in I^0} \frac{1}{c'_i}}}{c'_i} \right)^2 = \frac{\left(\theta_i - \bar{\theta}^0 + \frac{\bar{Q}^0 - Q^{*0}}{\sum_{i\in I^0} \frac{1}{c'_i}}\right)^2}{{c'_i}^2},$$

where

$$\bar{\theta}^0 \equiv \frac{\sum_{i\in I^0} \frac{\theta_i}{c'_i}}{\sum_{i\in I^0} \frac{1}{c'_i}};$$

for each "market" group $a = 1, \dots, A$, by $c'_i(q_i) \approx c'_i$, $x_i(q_i) \approx x_i$, $c_i(q_i^m) + \theta_i = p^{m^a}$ and $c_i(q_i^*) + \theta_i - x_i(q_i^*) = p^*$ for any $i \in I^a$, $\bar{Q}^a = \sum_{i\in I^a} q_i^m$, and $Q^{*a} \equiv \sum_{i\in I^a} q_i^*$, we have

$$(q_i^m - q_i^*)^2$$

$$\approx \left(\frac{\frac{\bar{Q}^a - \sum_{i\in I^a} \frac{-c_i(0) - \theta_i}{c'_i}}{\sum_{i\in I^a} \frac{1}{c'_i}} - c_i(0) - \theta_i}{c'_i} - \frac{\frac{Q^{*a} - \sum_{i\in I^a} \frac{x_i - c_i(0) - \theta_i}{c'_i}}{\sum_{i\in I^a} \frac{1}{c'_i}} + x_i - c_i(0) - \theta_i}{c'_i} \right)^2$$

$$= \left(-\frac{x_i - \frac{\sum_{i\in I^a} \frac{x_i}{c'_i}}{\sum_{i\in I^a} \frac{1}{c'_i}} - \frac{\bar{Q}^a - Q^{*a}}{\sum_{i\in I^a} \frac{1}{c'_i}}}{c'_i} \right)^2 = \frac{\left(x_i - \bar{x}^a - \frac{\bar{Q}^a - Q^{*a}}{\sum_{i\in I^a} \frac{1}{c'_i}}\right)^2}{{c'_i}^2},$$

where

$$\bar{x}^a \equiv \frac{\sum_{i \in I^a} \frac{x_i}{c'_i}}{\sum_{i \in I^a} \frac{1}{c'_i}}.$$

Here we see that for each group $a = 0, \ldots, A$, the complication is about $\bar{Q}^a - Q^{*a}$, i.e., ex ante missing the ex-post social-optimal allocation of targets across groups.

Now approximate Q^{*a} for each group $a = 0, \ldots, A$. From the proof of Lemma 2, by $c'_i(q_i) \approx c'_i$, $x_i(q_i) \approx x_i$, $c_i(q_i^*) + \theta_i - x_i(q_i^*) = p^*$ for any $i \in I$, and $Q = \sum_{i \in \mathrm{I}} q_i^*$, we have

$$q_i^* \approx \frac{\frac{Q - \sum_{i \in I} \frac{x_i - c_i(0) - \theta_i}{c'_i}}{\sum_{i \in I} \frac{1}{c'_i}} + x_i - c_i(0) - \theta_i}{c'_i}.$$

Therefore, by $Q^{*a} = \sum_{i \in I^a} q_i^*$, we have

$$Q^{*a} = \sum_{i \in I^a} q_i^* \approx \sum_{i \in I^a} \frac{\frac{Q - \sum_{i \in I} \frac{x_i - c_i(0) - \theta_i}{c'_i}}{\sum_{i \in \mathrm{I}} \frac{1}{c'_i}} + x_i - c_i(0) - \theta_i}{c'_i}.$$

Now approximate $\bar{Q}^a$ using Q. First, note that, for the "planning" group, we have approximated above

$$\bar{q}_i \approx \frac{\frac{\bar{Q}^0 - \sum_{i \in I^0} \frac{x_i - c_i(0)}{c'_i}}{\sum_{i \in I^0} \frac{1}{c'_i}} + x_i - c_i(0)}{c'_i};$$

for each "market" group $a = 1, \ldots, A$, we have approximated above

$$q_i^m \approx \frac{\frac{\bar{Q}^a - \sum_{i \in I^a} \frac{-c_i(0) - \theta_i}{c'_i}}{\sum_{i \in I^a} \frac{1}{c'_i}} - c_i(0) - \theta_i}{c'_i}.$$

Second, note that the first-order condition for the policy designer's program is, for any $a \in 1, \ldots, A$,

$$\frac{d\left(\sum_{i \in I^0}\left(\int_0^{\bar{q}_i}\left(c_i(q) - x_i(q)\right) dq\right)\right)}{d\bar{Q}^0} = \frac{d\mathbf{E}\left[\sum_{i \in I^a}\left(\int_0^{q_i^m}\left(c_i(q) + \theta_i - x_i(q)\right) dq\right)\right]}{d\bar{Q}^a}.$$

Note that for the "planning" group, by $x_i(\bar{q}_i) \approx x_i$ and $\bar{p}^0 = c_i(\bar{q}_i) - x_i(\bar{q}_i)$ for any $i \in I^0$, we have

$$\frac{d\left(\sum_{i\in I^0}\left(\int_0^{\bar{q}_i}\big(c_i(q) - x_i(q)\big)\,dq\right)\right)}{d\bar{Q}^0} = \bar{p}^0 = c_i(\bar{q}_i) - x_i(\bar{q}_i) \approx c_i(\bar{q}_i) - x_i;$$

for each "market" group $a = 1, \dots, A$, by $x_i(\bar{q}_i) \approx x_i$, $c_i(q_i^m) + \theta_i = p^{ma}$ for any $i \in I^a$, the approximation of q_i^m above, and $\mathbf{E}[\theta_i] = 0$, we have

$$\frac{d\mathbf{E}\left[\sum_{i\in I^a}\left(\int_0^{q_i^m}\big(c_i(q) + \theta_i - x_i(q)\big)\,dq\right)\right]}{d\bar{Q}^a} \approx \mathbf{E}[p^{ma}] - \frac{d\mathbf{E}[\sum_{i\in I^a} q_i^m\, x_i]}{d\bar{Q}^a}$$
$$= \mathbf{E}[c_i(q_i^m) + \theta_i] - \frac{\sum_{i\in I^a}\frac{x_i}{c'_i}}{\sum_{i\in I^a}\frac{1}{c'_i}} = \mathbf{E}[c_i(q_i^m)] - \bar{x}^a.$$

The first-order condition for the policy designer's program can thus be approximated by, for any $j \in I^0$, $k \in I^a$, and $a = 1, \dots, A$,

$$p \equiv c_j(\bar{q}_j) - x_j \approx \mathbf{E}[c_k(q_k^m)] - \bar{x}^a.$$

Third, by this approximated first-order condition and $c'_i(q_i) \approx c'_i$, for any $i \in I^0$, we have

$$c_i(0) + c'_i\bar{q}_i - x_i \approx p, \quad \text{i.e.,} \quad \bar{q}_i \approx \frac{p + x_i - c_i(0)}{c'_i},$$

and thus, by $\bar{Q}^0 = \sum_{i\in I^0}\bar{q}_i$, we have

$$\bar{Q}^0 \approx \sum_{i\in I^0}\frac{p + x_i - c_i(0)}{c'_i};$$

for any $i \in I^a$, where $a = 1, \dots, A$, we have

$$\mathbf{E}[c_i(0) + c'_i q_i^m] - \bar{x}^a \approx p, \quad \text{i.e.,} \quad \mathbf{E}[q_i^m] \approx \frac{p + \bar{x}^a - c_i(0)}{c'_i},$$

and thus, by $\bar{Q}^a = \sum_{i\in I^a} q_i^m$, we have

$$\bar{Q}^a = \sum_{i\in I^a}\mathbf{E}\,[q_i^m] \approx \sum_{i\in I^a}\frac{p + \bar{x}^a - c_i(0)}{c'_i}.$$

By $\sum_{a=0}^{A}\bar{Q}^a = Q$, we thus have

$$\sum_{i\in I^0}\frac{p+x_i-c_i(0)}{c'_i}+\sum_{a=1}^{A}\left(\sum_{i\in I^a}\frac{p+\bar{x}^a-c_i(0)}{c'_i}\right)\approx Q,$$

i.e.,

$$p\cdot\sum_{i\in I}\frac{1}{c'_i}-\sum_{i\in \mathrm{I}}\frac{c_i(0)}{c'_i}+\sum_{i\in I^0}\frac{x_i}{c'_i}+\sum_{a=1}^{A}\left(\sum_{i\in I^a}\frac{\bar{x}^a}{c'_i}\right)\approx Q,$$

i.e.,

$$p\approx\frac{Q+\sum_{i\in I}\frac{c_i(0)}{c'_i}-\sum_{i\in I^0}\frac{x_i}{c'_i}-\sum_{a=1}^{A}\left(\sum_{i\in I^a}\frac{\bar{x}^a}{c'_i}\right)}{\sum_{i\in \mathrm{I}}\frac{1}{c'_i}}=\frac{Q+\sum_{i\in \mathrm{I}}\frac{c_i(0)}{c'_i}}{\sum_{i\in \mathrm{I}}\frac{1}{c'_i}}-\bar{x},$$

where, by the definition of $\bar{x}^a$,

$$\bar{x}\quad\equiv\frac{\sum_{i\in I^0}\frac{x_i}{c'_i}+\sum_{a=1}^{A}\left(\sum_{i\in I^a}\frac{\bar{x}^a}{c'_i}\right)}{\sum_{i\in I}\frac{1}{c'_i}}=\frac{\sum_{i\in I^0}\frac{x_i}{c'_i}+\sum_{a=1}^{A}\left(\sum_{i\in I^a}\frac{\frac{\sum_{i\in I^a}\frac{x_i}{c'_i}}{\sum_{i\in I^a}\frac{1}{c'_i}}}{c'_i}\right)}{\sum_{i\in \mathrm{I}}\frac{1}{c'_i}}$$

$$=\frac{\sum_{i\in I^0}\frac{x_i}{c'_i}+\sum_{a=1}^{A}\left(\left(\sum_{i\in I^a}\frac{1}{c'_i}\right)\cdot\frac{\sum_{i\in I^a}\frac{x_i}{c'_i}}{\sum_{i\in I^a}\frac{1}{c'_i}}\right)}{\sum_{i\in \mathrm{I}}\frac{1}{c'_i}}=\frac{\sum_{i\in I^0}\frac{x_i}{c'_i}+\sum_{a=1}^{A}\left(\sum_{i\in I^a}\frac{x_i}{c'_i}\right)}{\sum_{i\in \mathrm{I}}\frac{1}{c'_i}}$$

$$=\frac{\sum_{i\in \mathrm{I}}\frac{x_i}{c'_i}}{\sum_{i\in \mathrm{I}}\frac{1}{c'_i}}.$$

Therefore, by the approximation of $\bar{Q}^a$ for each group $a=0,\dots,A$ above, we have, for the "planning" group,

$$\bar{Q}^0\approx\sum_{i\in I^0}\frac{\frac{Q+\sum_{i\in I}\frac{c_i(0)}{c'_i}}{\sum_{i\in \mathrm{I}}\frac{1}{c'_i}}-\bar{x}+x_i-c_i(0)}{c'_i}$$

and, for each "market" group $a = 1, \dots, A$,

$$\bar{Q}^a \approx \sum_{i \in I^a} \frac{\dfrac{Q + \sum_{i \in I} \dfrac{c_i(0)}{c'_i}}{\sum_{i \in \mathrm{I}} \dfrac{1}{c'_i}} - \bar{x} + \bar{x}^a - c_i(0)}{c'_i}.$$

Now we are ready to approximate $\bar{Q}^a - Q^{*a}$ for each group $a = 0, \dots, A$. For the "planning" group, by the definition of $\bar{x}$, we have

$$\begin{aligned}
\bar{Q}^0 - Q^{*0} \quad &\approx \sum_{i \in I^0} \frac{\dfrac{Q + \sum_{i \in I} \dfrac{c_i(0)}{c'_i}}{\sum_{i \in \mathrm{I}} \dfrac{1}{c'_i}} - \bar{x} + x_i - c_i(0)}{c'_i} \\
&\qquad - \sum_{i \in I^0} \frac{\dfrac{Q - \sum_{i \in \mathrm{I}} \dfrac{x_i - c_i(0) - \theta_i}{c'_i}}{\sum_{i \in \mathrm{I}} \dfrac{1}{c'_i}} + x_i - c_i(0) - \theta_i}{c'_i} \\
&= \sum_{i \in I^0} \frac{-\bar{x}}{c'_i} - \sum_{i \in I^0} \frac{\dfrac{-\sum_{i \in \mathrm{I}} \dfrac{x_i - \theta_i}{c'_i}}{\sum_{i \in \mathrm{I}} \dfrac{1}{c'_i}} - \theta_i}{c'_i} = \sum_{i \in I^0} \frac{\theta_i - \bar{\theta}}{c'_i},
\end{aligned}$$

where

$$\bar{\theta} \equiv \frac{\sum_{i \in I} \dfrac{\theta_i}{c'_i}}{\sum_{i \in \mathrm{I}} \dfrac{1}{c'_i}};$$

for each "market" group $a = 1, \dots, A$, we have

$$\bar{Q}^a - Q^{*a} \approx \sum_{i\in I^a} \frac{\dfrac{Q + \sum_{i\in I} \frac{c_i(0)}{c'_i}}{\sum_{i\in \mathrm{I}} \frac{1}{c'_i}} - \bar{x} + \bar{x}^a - c_i(0)}{c'_i}$$

$$- \sum_{i\in I^a} \frac{\dfrac{Q - \sum_{i\in \mathrm{I}} \frac{x_i - c_i(0) - \theta_i}{c'_i}}{\sum_{i\in \mathrm{I}} \frac{1}{c'_i}} + x_i - c_i(0) - \theta_i}{c'_i}$$

$$= \sum_{i\in I^a} \frac{-\bar{x} + \bar{x}^a}{c'_i} - \sum_{i\in I^a} \frac{\bar{\theta} + x_i - \bar{x} - \theta_i}{c'_i} = \sum_{i\in I^a} \frac{\theta_i - \bar{\theta} + \bar{x}^a - x_i}{c'_i}.$$

Now we are ready to further approximate ΔW^{Hybrid}. For $i \in I^0$, we have

$$(\bar{q}_i - q_i^*)^2 \approx \frac{\left(\theta_i - \bar{\theta}^0 + \dfrac{\bar{Q}^0 - Q^{*0}}{\sum_{i\in I^0} \frac{1}{c'_i}}\right)^2}{{c'_i}^2} \approx \frac{\left(\theta_i - \bar{\theta}^0 + \dfrac{\sum_{i\in I^0} \frac{\theta_i - \bar{\theta}}{c'_i}}{\sum_{i\in I^0} \frac{1}{c'_i}}\right)^2}{{c'_i}^2}$$

$$= \frac{(\theta_i - \bar{\theta}^0 + \bar{\theta}^0 - \bar{\theta})^2}{{c'_i}^2};$$

for $i \in I^a$, where $a = 1, \dots, A$, we have

$$(q_i^m - q_i^*)^2 \approx \frac{\left(x_i - \bar{x}^a - \dfrac{\bar{Q}^a - Q^{*a}}{\sum_{i\in I^a} \frac{1}{c'_i}}\right)^2}{{c'_i}^2} \approx \frac{\left(x_i - \bar{x}^a - \dfrac{\sum_{i\in I^a} \frac{\theta_i - \bar{\theta} + \bar{x}^a - x_i}{c'_i}}{\sum_{i\in I^a} \frac{1}{c'_i}}\right)^2}{{c'_i}^2}$$

$$= \frac{(x_i - \bar{x}^a - \bar{\theta}^a + \bar{\theta} - \bar{x}^a + \bar{x}^a)^2}{{c'_i}^2} = \frac{(x_i - \bar{x}^a - \bar{\theta}^a + \bar{\theta})^2}{{c'_i}^2},$$

where

$$\bar{\theta}^a \equiv \frac{\sum_{i\in I^a} \frac{\theta_i}{c'_i}}{\sum_{i\in I^a} \frac{1}{c'_i}}.$$

With all these at hand, by $c'(q_i) \approx c'_i$ and $x'(q_i) \approx 0$, we can approximate

$$
\begin{aligned}
\Delta W^{Hybrid} &\approx \frac{1}{2}\cdot (\sum_{i\in I^0} \mathbf{E}\left[\left(c'_i(q_i^*) - x'_i(q_i^*)\right)(\bar{q}_i - q_i^*)^2\right] \\
&\quad + \sum_{a=1}^{A}\left(\sum_{i\in I^a} \mathbf{E}\left[\left(c'_i(q_i^*) - x'_i(q_i^*)\right)(q_i^m - q_i^*)^2\right]\right)) \\
&\approx \frac{1}{2}\cdot\left(\sum_{i\in I^0}\mathbf{E}\left[c'_i\cdot\frac{(\theta_i-\bar{\theta}^0+\bar{\theta}^0-\bar{\theta})^2}{{c'_i}^2}\right] + \sum_{a=1}^{A}\left(\sum_{i\in I^a}\mathbf{E}\left[c'_i\cdot\frac{(x_i-\bar{x}^a-\bar{\theta}^a+\bar{\theta})^2}{{c'_i}^2}\right]\right)\right) \\
&= \frac{1}{2}\cdot\left(\sum_{i\in I^0}\mathbf{E}\left[\frac{(\theta_i-\bar{\theta}^0+\bar{\theta}^0-\bar{\theta})^2}{c'_i}\right] + \sum_{a=1}^{A}\left(\sum_{i\in I^a}\mathbf{E}\left[\frac{(x_i-\bar{x}^a-\bar{\theta}^a+\bar{\theta})^2}{c'_i}\right]\right)\right) \\
&= \frac{1}{2}\cdot\left(\sum_{i\in I^0}\left(\frac{1}{c'_i}\cdot\mathbf{E}[(\theta_i-\bar{\theta}^0+\bar{\theta}^0-\bar{\theta})^2]\right) + \sum_{a=1}^{A}\left(\sum_{i\in I^a}\left(\frac{1}{c'_i}\cdot\mathbf{E}[(x_i-\bar{x}^a-\bar{\theta}^a+\bar{\theta})^2]\right)\right)\right).
\end{aligned}
$$

Now calculate these variances. For any $i \in I^a$, where $a = 0, \ldots, A$, denote

$$
w_i \equiv \frac{\frac{1}{c'_i}}{\sum_{i\in I}\frac{1}{c'_i}}, \qquad \widetilde{w}_i \equiv \frac{\frac{1}{c'_i}}{\sum_{i\in I^a}\frac{1}{c'_i}},
$$

noting

$$
\sum_{i\in I} w_i = \sum_{i\in I^a}\widetilde{w}_i = 1.
$$

By $\mathbf{E}[\theta_i] = 0$ and θ_is' mutual independence, for $i \in I^0$, we have

$$\mathbf{E}[(\theta_i-\bar{\theta}^0+\bar{\theta}^0-\bar{\theta})^2]=\mathbf{E}\left[\left(\theta_i-\sum_{i\in I^0}\widetilde{w}_i\,\theta_i+\sum_{i\in I^0}\widetilde{w}_i\,\theta_i-\sum_{i\in I}w_i\,\theta_i\right)^2\right]$$

$$=\mathbf{E}[\left(\theta_i-\sum_{i\in I^0}\widetilde{w}_i\,\theta_i\right)^2+\left(\sum_{i\in I^0}\widetilde{w}_i\,\theta_i-\sum_{i\in \mathrm{I}}w_i\,\theta_i\right)^2$$

$$+2\left(\theta_i-\sum_{i\in I^0}\widetilde{w}_i\,\theta_i\right)\left(\sum_{i\in I^0}\widetilde{w}_i\,\theta_i-\sum_{i\in \mathrm{I}}w_i\,\theta_i\right)]$$

$$=\mathbf{E}[\left((1-\widetilde{w}_i)\theta_i-\sum_{j\in I^0\backslash\{i\}}\widetilde{w}_j\,\theta_j\right)^2+\left(\sum_{i\in I^0}(\widetilde{w}_i-w_i)\,\theta_i-\sum_{j\in \mathrm{I}\backslash I^0}w_j\,\theta_j\right)^2$$

$$+2\left((1-\widetilde{w}_i)\theta_i-\sum_{j\in I^0\backslash\{i\}}\widetilde{w}_j\,\theta_j\right)\left((\widetilde{w}_i-w_i)\theta_i+\sum_{j\in I^0\backslash\{i\}}\left(\widetilde{w}_j-w_j\right)\theta_j-\sum_{j\in \mathrm{I}\backslash I^0}w_j\,\theta_j\right)]$$

$$=(1-\widetilde{w}_i)^2\sigma_i^2+\sum_{j\in I^0\backslash\{i\}}\widetilde{w}_j{}^2\,\sigma_j^2+\sum_{i\in I^0}(\widetilde{w}_i-w_i)^2\,\sigma_i^2+\sum_{j\in \mathrm{I}\backslash I^0}w_j^2\,\sigma_j^2$$

$$+2\left((1-\widetilde{w}_i)(\widetilde{w}_i-w_i)\sigma_i^2-\mathbf{E}\left[\left(\sum_{j\in I^0\backslash\{i\}}\widetilde{w}_j\,\theta_j\right)\cdot\left(\sum_{j\in I^0\backslash\{i\}}\left(\widetilde{w}_j-w_j\right)\theta_j\right)\right]\right)$$

$$=(1-2\widetilde{w}_i)\sigma_i^2+\sum_{i\in I^0}\widetilde{w}_i{}^2\,\sigma_i^2+\sum_{i\in I^0}\widetilde{w}_i\,(\widetilde{w}_i-2w_i)\sigma_i^2+\sum_{i\in \mathrm{I}}w_i^2\,\sigma_i^2$$

$$+2\left((1-\widetilde{w}_i)(\widetilde{w}_i-w_i)\sigma_i^2-\sum_{j\in I^0\backslash\{i\}}\widetilde{w}_j\left(\widetilde{w}_j-w_j\right)\sigma_j^2\right)$$

$$=(1-2\widetilde{w}_i)\sigma_i^2+\sum_{i\in I^0}\widetilde{w}_i{}^2\,\sigma_i^2+\sum_{i\in I^0}\widetilde{w}_i\,(\widetilde{w}_i-2w_i)\sigma_i^2+\sum_{i\in \mathrm{I}}w_i^2\,\sigma_i^2$$

$$+2\left((\widetilde{w}_i-w_i)\sigma_i^2-\sum_{i\in I^0}\widetilde{w}_i\,(\widetilde{w}_i-w_i)\sigma_i^2\right);$$

for $i\in I^a$, where $a=1,\dots,A$, we have

$$\mathbf{E}[(x_i-\bar{x}^a-\bar{\theta}^a+\bar{\theta})^2]=(x_i-\bar{x}^a)^2+\mathbf{E}[(\bar{\theta}^a-\bar{\theta})^2]$$
$$=(x_i-\bar{x}^a)^2+\sum_{i\in I^a}\widetilde{w}_i\,(\widetilde{w}_i-2w_i)\sigma_i^2+\sum_{i\in I}w_i^2\,\sigma_i^2.$$

Denote

$$S\equiv\sum_{i\in I}\frac{1}{c'_i},\quad S^a\equiv\sum_{i\in I^a}\frac{1}{c'_i},$$

noting that

$$\sum_{a=0}^{A} S^a = S; \quad \text{for any } i \in I^a, Sw_i = S^a \widetilde{w}_i = \frac{1}{c'_i}.$$

We can now approximate the expected welfare loss by three parts. The first part is the approximated expected welfare loss from the "planning" group given the total allocation to the group. It is

$$\begin{aligned}
&\frac{1}{2} \cdot \left(\sum_{i \in I^0} \left(\frac{1}{c'_i} \cdot \left((1 - 2\widetilde{w}_i)\sigma_i^2 + \sum_{i \in I^0} \widetilde{w}_i^{\,2} \, \sigma_i^2 \right) \right) \right) \\
&= \frac{S^0}{2} \cdot \left(\sum_{i \in I^0} \left(\widetilde{w}_i \cdot \left((1 - 2\widetilde{w}_i)\sigma_i^2 + \sum_{i \in I^0} \widetilde{w}_i^{\,2} \, \sigma_i^2 \right) \right) \right) \\
&= \frac{S^0}{2} \cdot \left(\sum_{i \in I^0} \widetilde{w}_i \, (1 - 2\widetilde{w}_i)\sigma_i^2 + \left(\sum_{i \in I^0} \widetilde{w}_i \right) \cdot \left(\sum_{i \in I^0} \widetilde{w}_i^{\,2} \, \sigma_i^2 \right) \right) \\
&= \frac{S^0}{2} \cdot \left(\sum_{i \in I^0} \widetilde{w}_i \, (1 - 2\widetilde{w}_i)\sigma_i^2 + \sum_{i \in I^0} \widetilde{w}_i^{\,2} \, \sigma_i^2 \right) \\
&= \frac{S^0}{2} \cdot \left(\sum_{i \in I^0} \widetilde{w}_i \, (1 - \widetilde{w}_i)\sigma_i^2 \right) \equiv \frac{S^0}{2} \cdot V_\theta^0.
\end{aligned}$$

The second part is the approximated expected welfare loss from the "market" groups given the total allocation to each of them. It is

$$\begin{aligned}
&\frac{1}{2} \cdot \left(\sum_{a=1}^{A} \left(\sum_{i \in I^a} \left(\frac{1}{c'_i} \cdot (x_i - \bar{x}^a)^2 \right) \right) \right) = \frac{1}{2} \cdot \left(\sum_{a=1}^{A} \left(S^a \cdot \left(\sum_{i \in I^a} \widetilde{w}_i \, (x_i - \bar{x}^a)^2 \right) \right) \right) \\
&= \sum_{a=1}^{A} \left(\frac{S^a}{2} \cdot \left(\sum_{i \in I^a} \widetilde{w}_i \, (x_i - \bar{x}^a)^2 \right) \right) \equiv \sum_{a=1}^{A} \left(\frac{S^a}{2} \cdot D_x^a \right).
\end{aligned}$$

The third part is the approximated expected welfare loss from the potential misallocation of total targets across all groups. It is

$$\frac{1}{2}\cdot\left(\sum_{a=0}^{A}\left(\sum_{i\in I^a}\left(\frac{1}{c'_i}\cdot\left(\sum_{i\in I^a}\widetilde{w}_i\,(\widetilde{w}_i-2w_i)\sigma_i^2+\sum_{i\in I}w_i^2\,\sigma_i^2\right)\right)\right)\right)$$
$$+\frac{1}{2}\cdot\left(\sum_{i\in I^0}\left(\frac{1}{c'_i}\cdot 2\left((\widetilde{w}_i-w_i)\sigma_i^2-\sum_{i\in I^0}\widetilde{w}_i\,(\widetilde{w}_i-w_i)\sigma_i^2\right)\right)\right)$$
$$=\frac{1}{2}\cdot\left(\sum_{a=0}^{A}\left(\sum_{i\in I^a}\left(\frac{1}{c'_i}\cdot\left(\sum_{i\in I^a}\widetilde{w}_i\,(\widetilde{w}_i-2w_i)\sigma_i^2+\sum_{i\in \mathrm{I}}w_i^2\,\sigma_i^2\right)\right)\right)\right)$$
$$+\sum_{i\in I^0}\left(\frac{1}{c'_i}\cdot\left((\widetilde{w}_i-w_i)\sigma_i^2-\sum_{i\in I^0}\widetilde{w}_i\,(\widetilde{w}_i-w_i)\sigma_i^2\right)\right).$$

The first half is

$$\frac{1}{2}\cdot\left(\sum_{a=0}^{A}\left(\sum_{i\in I^a}\left(\frac{1}{c'_i}\cdot\left(\sum_{i\in I^a}\widetilde{w}_i\,(\widetilde{w}_i-2w_i)\sigma_i^2+\sum_{i\in I}w_i^2\,\sigma_i^2\right)\right)\right)\right)$$
$$=\frac{1}{2}\cdot\left(\sum_{a=0}^{A}\left(S^a\cdot\left(\sum_{i\in I^a}\left(\widetilde{w}_i\cdot\left(\sum_{i\in I^a}\widetilde{w}_i\,(\widetilde{w}_i-2w_i)\sigma_i^2+\sum_{i\in \mathrm{I}}w_i^2\,\sigma_i^2\right)\right)\right)\right)\right)$$
$$=\frac{1}{2}\cdot\left(\sum_{a=0}^{A}\left(S^a\cdot\left(\sum_{i\in I^a}\widetilde{w}_i\right)\cdot\left(\sum_{i\in I^a}\widetilde{w}_i\,(\widetilde{w}_i-2w_i)\sigma_i^2+\sum_{i\in \mathrm{I}}w_i^2\,\sigma_i^2\right)\right)\right)$$
$$=\frac{1}{2}\cdot\left(\sum_{a=0}^{A}\left(S^a\cdot\left(\sum_{i\in I^a}\widetilde{w}_i\,(\widetilde{w}_i-2w_i)\sigma_i^2\right)+S^a\cdot\left(\sum_{i\in \mathrm{I}}w_i^2\,\sigma_i^2\right)\right)\right)$$
$$=\frac{1}{2}\cdot\left(\sum_{a=0}^{A}\left(S\cdot\left(\sum_{i\in I^a}w_i\,(\widetilde{w}_i-2w_i)\sigma_i^2\right)+S^a\cdot\left(\sum_{i\in \mathrm{I}}w_i^2\,\sigma_i^2\right)\right)\right)$$
$$=\frac{1}{2}\cdot\left(S\cdot\left(\sum_{i\in \mathrm{I}}w_i\,(\widetilde{w}_i-2w_i)\sigma_i^2\right)+\left(\sum_{a=0}^{A}S^a\right)\cdot\left(\sum_{i\in \mathrm{I}}w_i^2\,\sigma_i^2\right)\right)$$
$$=\frac{S}{2}\cdot\left(\sum_{i\in \mathrm{I}}w_i\,(\widetilde{w}_i-2w_i)\sigma_i^2+\sum_{i\in \mathrm{I}}w_i^2\,\sigma_i^2\right)$$
$$=\frac{S}{2}\cdot\left(\sum_{i\in I}w_i\,(\widetilde{w}_i-w_i)\sigma_i^2\right).$$

The second half is

$$\sum_{i\in I^0}\left(\frac{1}{c'_i}\cdot\left((\widetilde{w}_i - w_i)\sigma_i^2 - \sum_{i\in I^0}\widetilde{w}_i\,(\widetilde{w}_i - w_i)\sigma_i^2\right)\right)$$

$$= S^0\cdot\left(\sum_{i\in I^0}\left(\widetilde{w}_i\cdot\left((\widetilde{w}_i - w_i)\sigma_i^2 - \sum_{i\in I^0}\widetilde{w}_i\,(\widetilde{w}_i - w_i)\sigma_i^2\right)\right)\right)$$

$$= S^0\cdot\left(\sum_{i\in I^0}\widetilde{w}_i\,(\widetilde{w}_i - w_i)\sigma_i^2 - \left(\sum_{i\in I^0}\widetilde{w}_i\right)\cdot\left(\sum_{i\in I^0}\widetilde{w}_i\,(\widetilde{w}_i - w_i)\sigma_i^2\right)\right)$$

$$= S^0\cdot\left(\sum_{i\in I^0}\widetilde{w}_i\,(\widetilde{w}_i - w_i)\sigma_i^2 - \sum_{i\in I^0}\widetilde{w}_i\,(\widetilde{w}_i - w_i)\sigma_i^2\right) = 0.$$

Therefore, the third part is just

$$\frac{S}{2}\cdot\left(\sum_{i\in I} w_i\,(\widetilde{w}_i - w_i)\sigma_i^2\right) \equiv \frac{S}{2}\cdot\tilde{V}_\theta.$$

To summarize, we have

$$\Delta W^{Hybrid} \approx \frac{S^0}{2}\cdot V_\theta^0 + \sum_{a=1}^{A}\left(\frac{S^a}{2}\cdot D_x^a\right) + \frac{S}{2}\cdot\tilde{V}_\theta,$$

where, for any $i \in I^a$,

$$w_i \equiv \frac{\frac{1}{c'_i}}{\sum_{i\in \bigcup_{a=0}^{A} I^a}\frac{1}{c'_i}},\quad \widetilde{w}_i \equiv \frac{\frac{1}{c'_i}}{\sum_{i\in I^a}\frac{1}{c'_i}};$$

for any $a = 0, \dots, A$,

$$S^a \equiv \sum_{i\in I^a}\frac{1}{c'_i},\quad V_\theta^a \equiv \sum_{i\in I^a}\widetilde{w}_i\,(1-\widetilde{w}_i)\sigma_i^2,\quad \bar{x}^a \equiv \sum_{i\in I^a}\widetilde{w}_i\,x_i,\quad D_x^a \equiv \sum_{i\in I^a}\widetilde{w}_i\,(x_i - \bar{x}^a)^2;$$

$$S \equiv \sum_{i\in I}\frac{1}{c'_i},\quad \tilde{V}_\theta \equiv \sum_{i\in \mathrm{I}} w_i\,(\widetilde{w}_i - w_i)\sigma_i^2.$$

The proposition is thus proven.

Appendix G. Estimating the Marginal Abatement Costs of Carbon Using Directional Distance Function Approach

We obtain the Marginal Abatement Cost (MAC) by the Directional Distance Function (DDF) approach, which estimates the monetary value of CO_2 emission by examining the production tradeoffs between two types of outputs, GDP (desired output) and CO_2 emissions (undesirable output) (Chung, Färe, and Grosskopf 1997; Färe et al. 1993a, 2005).

This method begins with an environmental production technology frontier: the producer employs a vector of inputs x to produce the desired GDP, $y,$ and undesired CO_2, b:

$$P(x) = \{(y, b): x \text{ can produce } (y, b)\}.$$ [16]

The output set assumes that if $(y, b) \epsilon P(x)$ and $b = 0$, then $y = 0$, which treats the undesired polluting CO_2 as a weakly disposable output and implies that the desirable output cannot be produced if no undesired CO_2 is produced. In other words, it is costly to reduce the undesired CO_2 and any proportional reduction of desired and undesired output is feasible, i.e., $(\theta y, \theta b) \in P(x)$ for $0 \leq \theta \leq 1$.

Given this production possibility set, we can use the Shephard output distance functions to represent technology (Shepherd 1971). A generalized output distance function can be defined as

$$\overrightarrow{D_0}(x, y, b, g_y, -g_b) = \max\{\beta: (y + \beta g_y, b - \beta g_b\} \in P(x),$$

where $(g_y, -g_b)$ is a pre-specified directional vector measuring the max amount by which an input-output vector can be translated while remaining technically feasible. The DDF takes a value of zero when the unit is on the frontier or efficient.

This DDF approach implies that an increase of g_y units in GDP is linked to g_b units of abatement in CO_2 emissions. Thus, the MAC can be interpreted as the shadow price of CO_2 emissions. The choice of the directional vector $(g_y, -g_b)$ shows the social planner's policy preference.[17] After choosing the directional vector and function form of

[16] In practice we use the labor, capital stock, and energy consumption as the production inputs.

[17] We set the directional vector as $(g_y, -g_b) = (1, -1)$ to seek a simultaneous expansion of the good output and a reduction of bad output.

the DDF, the shadow price of carbon q_b (i.e., the marginal abatement cost) can be inferred by using the duality between the DDF and the revenue function (or cost function):

$$q_b = -p_y \left[\frac{\partial \overrightarrow{D_0}(x, y, b; 1, -1)/\partial b}{\partial \overrightarrow{D_0}(x, y, b; 1, -1)/\partial y} \right],$$

where p_y is the monetary value of GDP. In other words, the MAC of carbon emissions is equal to the ratio of the partial derivative of the DDF with respect to the desirable output. The partial derivative can be estimated either nonparametrically or parametrically. The nonparametric estimation is based on data envelopment analysis (DEA). The parametric estimation process specifies the function form of the DDF and is based on a deterministic linear programming algorithm or the stochastic frontier analysis (Aigner and Chu 1968; Färe et al. 2005).

In practice, we use a quadratic functional form of the DDF:

$$\overrightarrow{D_0}(x_i^t, y_i^t, b_i^t; 1, -1)$$
$$= \alpha + \sum_{n=1}^{3} \alpha_n x_{ni}^t + \beta_1 y_i^t + \gamma_1 b_i^t + \frac{1}{2} \sum_{n}^{3} \sum_{n'}^{3} \alpha_{nn'} x_{ni}^t x_{n'i}^t + \frac{1}{2} \beta_2 (y_i^t)^2$$
$$+ \frac{1}{2} \gamma_2 (b_i^t)^2 + \sum_{n=1}^{3} \eta_n x_{ni}^t b_i^t + \sum_{n=1}^{3} \delta_n x_{ni}^t y_i^t + \mu y_i^t b_i^t,$$

where x_{ni}^t refer to the province i's production inputs in year t ($n = 1,2,3$: labor, capital stock, and energy consumption). y_i^t and b_i^t represent the GDP and CO_2 emissions, respectively. Province fixed effects and year fixed effects are controlled in the model to eliminate the province-specific time-invariant confounders as well as the time-variant shocks that applied to all provinces in the same year. As indicated earlier, the parameters in the DDF can be estimated through a deterministic linear programming algorithm, which seeks to minimize the sum of the deviations of the estimated distance functions from their frontier (Aigner and Chu 1968). Additionally, the following parametric restrictions are imposed to reflect the properties of feasibility, monotonicity, homogeneity, translation, and symmetry:

(1) $\overrightarrow{D_0}(x_i^t, y_i^t, b_i^t; 1, -1) \geq 0$, ensuring that all sets of the production possibility are within the frontiers;

(2) $\overrightarrow{D_0}(x_i^t, y_i^t, 0; 1, -1) < 0$, ensuring that the generating GDP involves emitting CO_2, i.e., $(y_i^t, 0)$, will be impossible if $y_i^t > 0$;

(3) $\frac{\partial \overrightarrow{D_0}(x_i^t, y_i^t, b_i^t; 1, -1)}{\partial b} \geq 0$ and $\frac{\partial \overrightarrow{D_0}(x_i^t, y_i^t, b_i^t; 1, -1)}{\partial y} \leq 0$, implying that the sign of the carbon price should be consistent with the sign of GDP;

(4) $\frac{\partial \overrightarrow{D_0}(\bar{x}, y_i^t, b_i^t; 1, -1)}{\partial x_n} \geq 0$, imposing positive monotonicity constraints on the usage of the inputs, that the DDF will increase along with the increase in inputs, holding outputs constant;

and, in addition, two properties of the function:

(5) $\beta_1 - \gamma_1 = -1,\ \beta_2 = \gamma_2 = \mu,\ \delta_n - \eta_n = 0$;

(6) $\alpha_{n,n'} = \alpha_{n',n},\ n, n' = 1,2,3.$

Figure S1 summarizes our estimated Marginal Abatement Cost (MAC) for each province in 2017. The monetary values here are all adjusted to the 2015 level. We find that Tianjin, Jilin, Fujian, Henan, Yunnan, and some other provinces have relatively higher MAC, while the MACs are lower in Anhui, Shanxi, Sichuan, and Jiangsu. The median MAC is 747.3 USD/Ton. Tianjin has the highest marginal costs of carbon abatement, which is about four times higher than the lowest one, Anhui. In Figure S2, we plot the trends in carbon emission intensity, energy consumption intensity, and marginal abatement cost of carbon from 2000 to 2017. From 2000 to 2017, the MAC increased about 1.5 times. In particular, we find that the MAC has significantly and consistently increased since 2011, the beginning year of the 12th Five-Year-Plan.

The DDF method is widely used by the China's scholars to estimate the MAC at both regional and industrial scales (Ma, Hailu, and You 2019). As suggested by the literature, the DDF is believed to be more appropriate in estimating the MAC due to its ability to model the productivity adjustments under environmental regulation (Färe et al. 1993b; Färe and Primont 1995). In Figure S4, we compare our MAC estimate with those in the literature and find that our estimates are comparable to the mean of these estimates.

By comparing the magnitude of the estimated MAC with the carbon price in the pilot trading scheme markets, we can find that the carbon price in China's carbon market, which is lower than 100 CNY per ton, or 15 USD per ton, is substantially lower. There are several reasons. For example, China's ongoing carbon market is a Tradable Performance Standard (TPS) instrument that targets emission intensity, which is different from the classic Cap-and-Trade (CAT) instrument. In other words, the "cap" constraints for the firms in the carbon market may be unbinding, which is consistent with a low carbon price. In addition, carbon price on the market also depends on market participants' expectation. Anticipated investment in carbon reduction technologies in the future will also reduce the present value of expected marginal abatement cost. The discrepancy between estimated MAC and market price may also come from the estimation process. As suggested by Ma and Hailu (2016), the DDF estimates are closer to the long-run marginal abatement costs, while the carbon price in the carbon market usually only reflects firms' costs in the short run.

Appendix H. Monetize the Air Pollution-Related Local External Cost of Carbon Emissions

Using the estimated carbon-air pollutant emission elasticity in Table 2, we can calculate the air-pollution-related local external costs for each province. Our calculation is based on the estimates from four recent quasi-experimental studies in China.

(1) Pre-mature Deaths

Fan, He, and Zhou (2020) document that a 10-point increase in AQI can increase the weekly mortality by 3.8%. With this estimate, we calculate the number of pre-mature deaths for each province caused by:

$$Deaths_i = \frac{\beta_{AQI-Carbon} * M_{i,2017} * AQI_{i,2017}}{10} * MR * 3.8\% * Pop_i * 52$$

where $\beta_{AQI-Carbon}$ represents the estimated carbon emission-AQI elasticity in Table 3, i.e., 1% increase in CO_2 emissions are related to 0.33% increase in AQI levels. M_i is a fraction calculated by the marginal percentage change in carbon emissions, $\frac{\text{1 ton}}{\text{CO}_2 \text{ Emissions in Province } i \text{ in 2017}}$. $AQI_{i,2017}$ is the AQI levels in province *i* in 2017. Hence, $\beta_{AQI-Carbon} * M_{i,2017} * AQI_{i,2017}$ caculates the increase in AQI levels related to 1 ton's increase in CO_2 emissions. MR is the weekly mortality rate, and we borrow this number (10.98 per 100,000) from (Fan, He, and Zhou 2020).[18] Pop_i is the population size in province *i* in 2017. We then multiply the numbers by 52 (about 52 weeks in one year) to get the yearly pre-mature deaths from the increase in AQI.

Column (2) in Table S3 summarizes the estimated annual pre-mature deaths in each province associated with one million tons increase in CO_2 emissions.[19] We find that on average it can cause 75.75 pre-mature deaths in each province. To monetarize the cost from mortality, we use the value of a statistical life (VSL), which is measured by people's willingness to pay to reduce the risk of dying. We follow Fan, He, and Zhou (2020)'s

[18] This weekly mortality rate is calculated from 617 million residents living in 13 northern provinces using the data in 2014 and 2015.

[19] One million tons of CO_2 emissions is about ten-thousandth of the total CO_2 emissions in China in 2017.

strategy to assigning VSL to pre-mature deaths caused by air pollution and borrow VSL estimate from Qin, Li, and Liu (2013).

$$Cost\_Death_i = Deaths_i * VSL * 70\%$$

where VSL is the adjusted value of a statistical life in 2015 price, 7.45 million CNY. We then discount the results by 70% to provide a lower and conservative estimate, assuming that only the elderly people suffered from the increase in death risk. In Column (3) of Table S3, we calculate that increasing one million tons of CO_2 emissions can cause on average an annual cost of 60.73 million USD for polluted-related pre-mature deaths.

(2) Morbidity costs

Barwick et al. (2018)'s research finds that 10-$\mu g/m^3$ reduction in $PM_{2.5}$ can save 73.45 CNY (in 2015 price) for each household's annual healthcare expenditure. Hence, we calculate the morbidity cost for each province by the following equation:

$$Cost\_Morbidity_i = \frac{\beta_{PM2.5-Carbon} * M_{i,2017} * PM2.5_{i,2017}}{10} * Pop_i/3 * 73.45$$

where $\beta_{PM2.5-Carbon}$ is the estimated carbon emission-$PM_{2.5}$ elasticity in Table 3, i.e., 1% increase in CO_2 emissions are related to 0.36% increase in $PM_{2.5}$ levels. $PM2.5_{i,2017}$ is the $PM_{2.5}$ concentration levels in province *i* in 2017. We assume on average each household has three individuals. In Column (4) of Table S3, we summarize the local morbidity cost associated with from one million tons of CO_2 emissions in each province. We find the average polluted-related morbidity cost caused by carbon emissions is 0.91 million USD per year.

(3) Defensive expenditure

Ito and Zhang (2020) find that a China's household is willing to pay 8.71 CNY (in 2015 price) annually to remove PM_{10} by 1-$\mu g/m^3$. Using a similar strategy in computing the morbidity cost, we use this estimate to find out the defensive expenditure in avoiding PM_{10}:

$$Cost\_Defensive_i = \beta_{PM10-Carbon} * M_{i,2017} * PM10_{i,2017} * Pop_i/3 * 8.71.$$

Column (5) of Table S3 summarizes the defensive expenditure from one million tons emissions of CO_2 in each province.

(4) Economic Costs due to Loss in Productivity

Fu, Viard, and Zhang (2021) study the air pollution's impacts on firm's productivity. Their results document that a 1% reduction in $PM_{2.5}$ can increase annually GDP by 0.038%. We use the following equation to compute the economic cost:

$$Cost\_GDP_i = \beta_{PM2.5-Carbon} * 0.038\% * GDP_{i,2017}$$

where $GDP_{i,2017}$ is the GDP in each province in 2017. Column 6 of Table S3 summarizes the corresponding results, where we find that one million tons emissions of CO_2 can reduce the GDP by 19.15 million USD on average.

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Appendix Tables and Figures

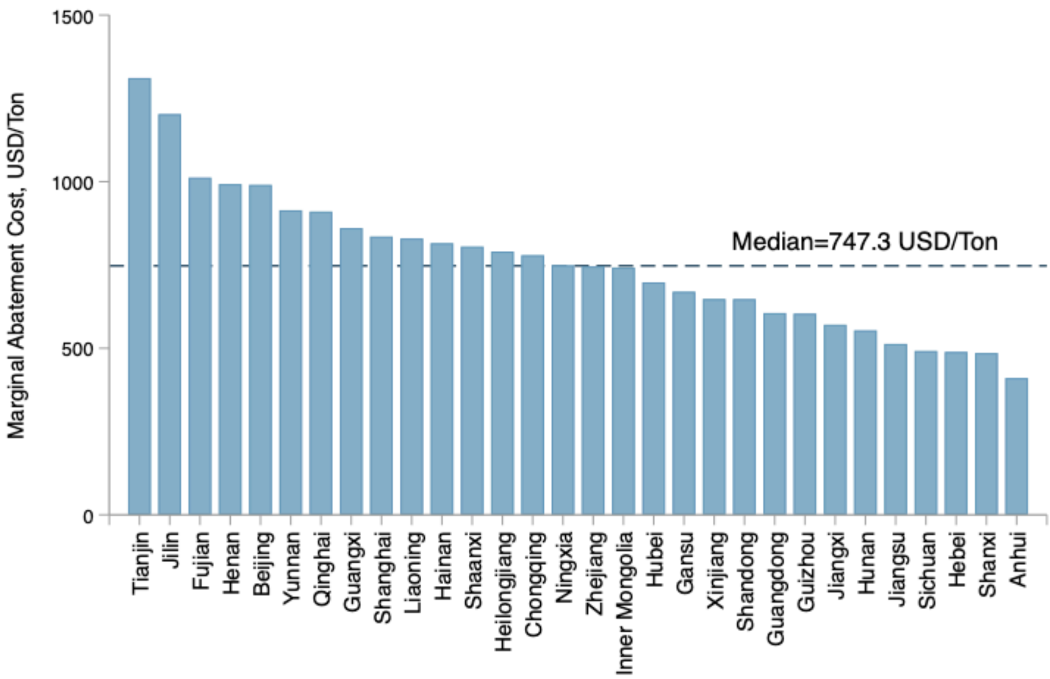


Figure S1. Estimated Provincial Marginal Abatement Cost (MAC) of Carbon Emissions in 2017

Notes: GDP is deflated to the Year 2015 level using China's Consumer Price Index. 1 USD = 6.5138 CNY.

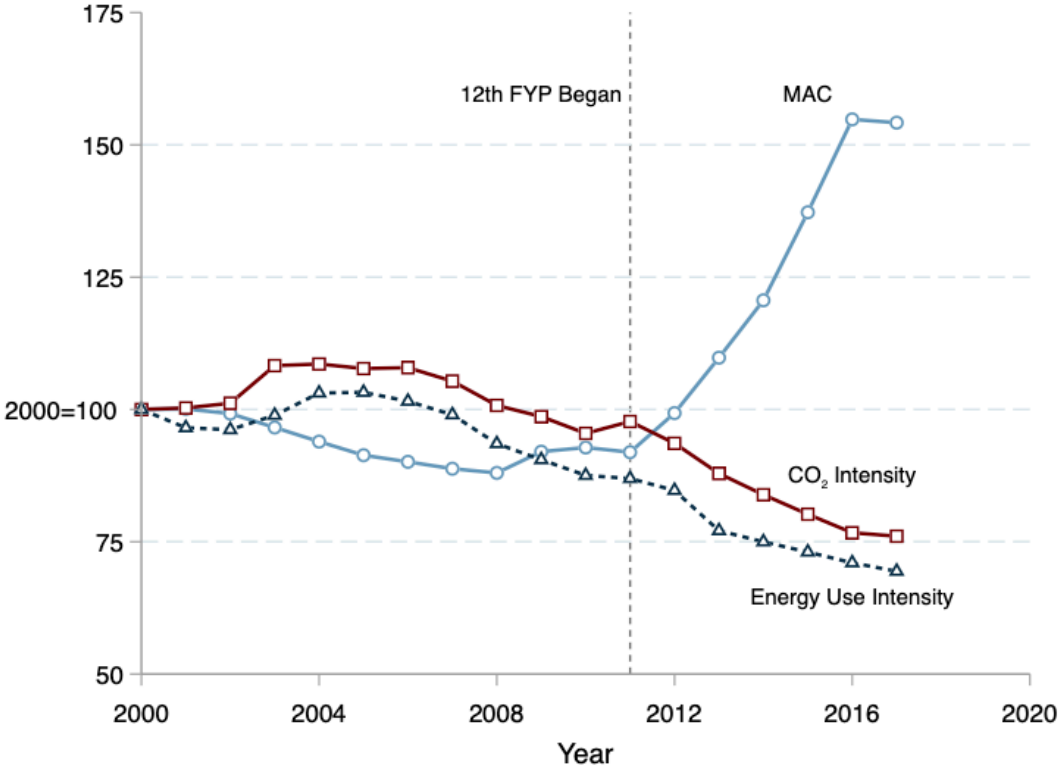
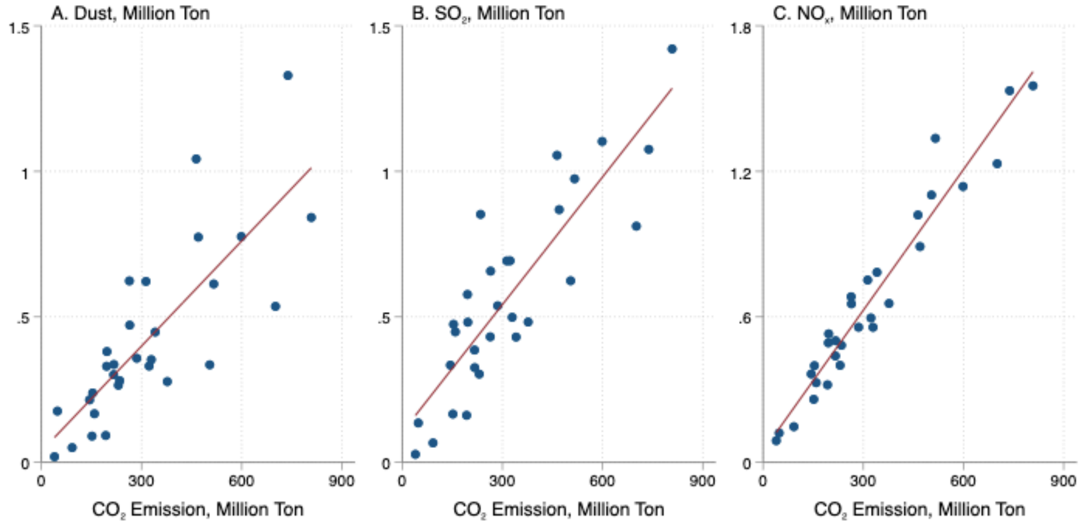


Figure S2. Trends of Intensity Measures and Estimated MACs of CO_2 Emissions (2000–2017)

Panel A. Provincial CO_2 Emissions and Emissions of Air Pollutants (2011-2017)



Panel B. Provincial CO_2 Emissions and Air Quality Levels (2015-2017)

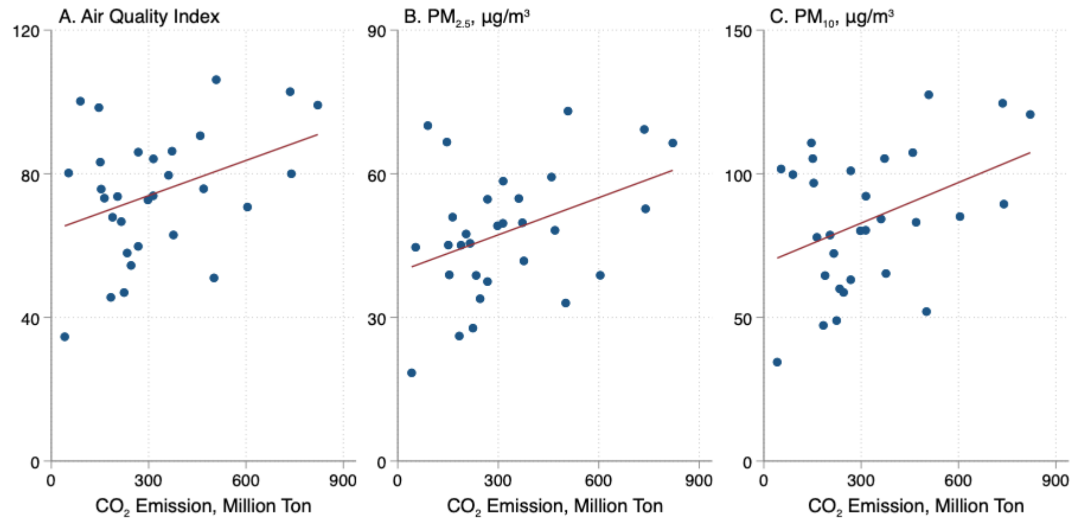


Figure S3. Carbon Emissions and Air Pollution

Notes: Each dot represents a province. Panel A plots the relationship between carbon emissions and the emissions of different air pollutants using provincial data. We take the averages of these variables from 2011 to 2017 to plot the figure. Panel B plots the relationship between carbon emissions and ambient air quality measures using provincial data. We take the averages of these variables from 2015 to 2017 to plot the figure. AQI (Air Quality Index) is a comprehensive measure of air pollution used by the Chinese government. Details about the AQI can be found in Table S1.

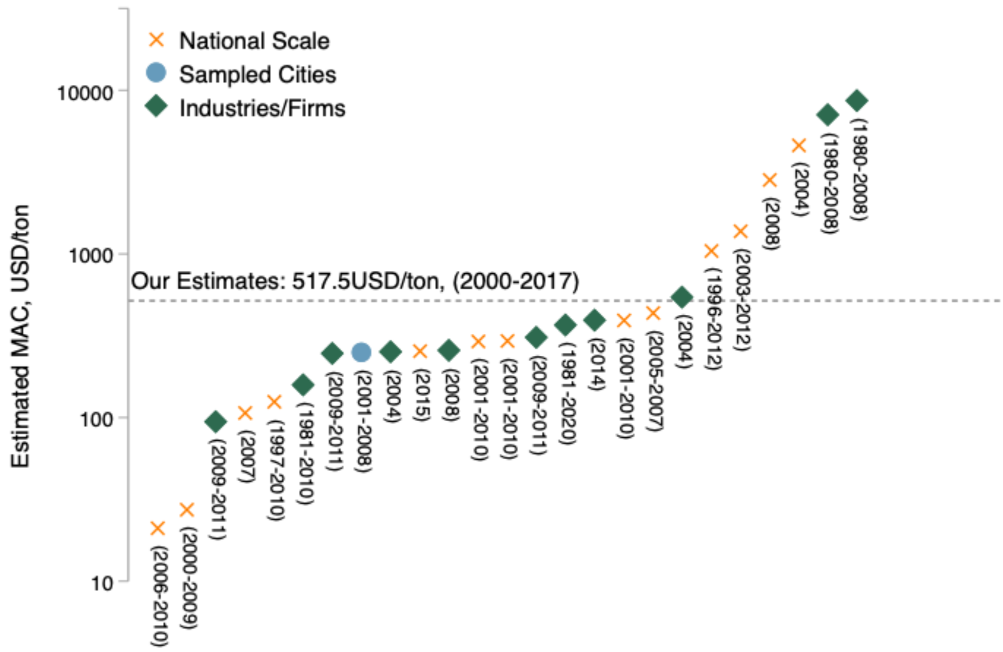


Figure S4. Estimates of Marginal Abatement Cost in the Literature

Notes: Each point represents an average estimates of marginal abatement cost from different literature. From left to right, these estimates are plotted according to their magnitude from the smallest to the largest. The parenthesis below each point indexes the corresponding covered period in the literature. The horizontal dashed line indicates our estimates over the period 2000 to 2017. All the monetary values are deflated to year 2015. Literature from left to right: Zhang et al. (2014), He (2015), Zhou, Fan, and Zhou (2015), Wang et al. (2011), Wang et al. (2014), Chen (2013), Zhou, Fan, and Zhou (2015), Wei (2014), Du and Mao (2015), Chen and Yang (2015), Du and Mao (2015), Du, Hanley, and Wei (2015a), Du, Hanley, and Wei (2015b), Zhou, Fan, and Zhou (2015), Chen (2013), Wang et al. (2017), Ma and Hailu (2016), Liu, Zhu, and Fan (2011), Wei, Löschel, and Liu (2013), Wang et al. (2016), Tang, Yang, and Zhang (2016), Yuan, Liang, and Cheng (2012), Yuan, Liang, and Cheng (2012), Chen (2010), and Chen (2010). Some literatures are duplicated as they produced more than one MAC estimates.

Table S1. AQI and Air Pollutant Concentrations (mg/m^3)

AQI	SO_2	NO_2	PM_{10}	CO	O_3	Air Quality Levels
0-50	0-0.050	0-0.080	0-0.050	0-5	0-0.120	Excellent
50-100	0.050-0.150	0.080-0.120	0.050-0.150	5-10	0.120-0.200	Good
100-200	0.150-0.800	0.120-0.280	0.150-0.350	10-60	0.200-0.400	Slightly Polluted
200-300	0.800-1.600	0.280-0.565	0.350-0.420	60-90	0.400-0.800	Moderately Polluted
300-400	1.600-2.100	0.565-0.750	0.420-0.50	90-120	-	Severely Polluted
400-500	2.100-2.620	0.750-0.940	0.500-0.600	120-150	-	Severely Polluted

Notes: The AQI is determined by the maximum concentrations of different air pollutants. This table reports the AQI sub-index levels for each air pollutant. The sub-index with the highest value will then be used as the AQI.

Table S2. The Correlations between CO_2 Emissions and Air Pollutants

	Industrial Dust (Ton, log)		SO_2 (Ton, log)		NO_x (Ton, log)	
	(1)	(2)	(3)	(4)	(5)	(6)
CO_2 Emissions	0.49**	0.49**	0.97***	0.96***	0.30**	0.30**
(Million Ton, log)	(0.19)	(0.19)	(0.30)	(0.30)	(0.14)	(0.14)
R-Squared	0.98	0.98	0.97	0.97	0.99	0.99
Weather Controls		Y		Y		Y
Province Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	210	210	210	210	210	210
Number of Provinces	30	30	30	30	30	30

Notes: Each column reports a separate regression on the correlation between CO_2 emissions and different air pollutant emissions using the provincial data from 2011 to 2017. The independent variable is the logarithm of annual CO_2 emission levels, and the dependent variables are the logarithms of different air pollutant emissions. Weather controls include temperature and precipitation levels. Standard errors in parentheses are clustered at the province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S3. The Air Pollution-Related Local External Cost of Carbon Emissions

Province Name	Pre-Mature Deaths (Number)	Monetary Values of (2) (Annually)	Morbidity Expenditures (Annually)	Defensive Expenditures (Annually)	Economic Cost (Annually)	Reduced Life Expectancy (Thousand Years)	Monetary Values of (7) (Million USD)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beijing	156.00	125.06	1.97	4.14	66.56	335.21	3947.61
Tianjin	73.27	58.74	0.93	2.07	26.63	158.00	1860.73
Hebei	71.46	57.29	0.89	2.22	10.00	152.03	1790.36
Shanxi	51.04	40.92	0.63	1.57	6.20	107.58	1266.88
Inner Mongolia	18.40	14.75	0.18	0.57	4.71	31.48	370.70
Liaoning	46.29	37.11	0.54	1.27	10.09	91.74	1080.43
Jilin	63.89	51.22	0.75	1.73	15.14	127.67	1503.58
Heilongjiang	59.36	47.59	0.71	1.61	12.16	120.66	1420.98
Shanghai	55.16	44.22	0.65	1.34	32.03	111.07	1308.02
Jiangsu	59.23	47.49	0.73	1.66	23.57	123.53	1454.80
Zhejiang	62.38	50.01	0.76	1.65	27.37	129.75	1528.00
Anhui	98.95	79.33	1.27	2.75	14.98	216.90	2554.36
Fujian	56.84	45.57	0.63	1.51	28.36	106.67	1256.25
Jiangxi	99.67	79.90	1.30	2.76	18.77	220.59	2597.84
Shandong	79.08	63.40	0.95	2.44	18.21	162.53	1914.05

Henan	136.04	109.06	1.73	4.11	18.39	294.45	3467.64
Hubei	99.72	79.95	1.29	2.73	22.70	220.04	2591.31
Hunan	108.70	87.14	1.37	3.02	22.54	233.39	2748.55
Guangdong	75.43	60.47	0.92	1.96	33.49	156.66	1844.89
Guangxi	90.53	72.58	1.15	2.38	18.64	195.78	2305.67
Hainan	52.27	41.91	0.53	1.31	21.46	90.23	1062.64
Chongqing	92.68	74.30	1.17	2.50	24.93	198.82	2341.41
Sichuan	133.76	107.24	1.67	3.67	24.17	284.47	3350.11
Guizhou	52.60	42.17	0.60	1.45	10.72	102.75	1210.06
Yunnan	79.07	63.39	0.83	2.11	17.12	141.65	1668.19
Shaanxi	88.76	71.16	1.07	2.61	16.88	182.61	2150.47
Gansu	89.98	72.14	0.82	2.97	9.98	139.79	1646.26
Qinghai	61.41	49.23	0.58	2.01	9.39	98.52	1160.18
Ningxia	22.64	18.15	0.22	0.75	3.97	38.02	447.71
Xinjiang	37.84	30.34	0.41	1.16	5.44	70.31	827.97
Average	75.75	60.73	0.91	2.13	19.15	154.76	1822.59

Notes: Each province's local external costs of carbon emissions are calculated using the procedures documented in Appendix H. Columns (2) to (6) summarize annual short-term external costs based on pre-mature deaths, health-care spending, defensive expenditure, and loss in productivity. Columns (7) and (8) summarize long-term external costs based on loss in life expectancy. The values in Columns (3)–(6) and Column (8) is measured by million USD (deflated to the 2015 level).