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

GUOJUN HE YUHANG PAN YANG XIE

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We revisit the classic "market vs. planning" debate in economic coordination in the context of achieving a pre-determined target of emission abatement, by comparing a Cap-and-Trade market versus an ex-ante optimal allocative plan of non-tradable permits. We show that the market can address incomplete information about the abatement cost, but not heterogeneous local externalities of abatement, while the opposite is true for planning, constituting a trade-off in policy design. Applying the theoretical results to China's carbon abatement, we find that a hybrid scheme that combines subnational planning with segregated subnational markets can improve upon both the market- and planning-alone approaches.

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

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* He: Faculty of Business and Economics, University of Hong Kong (email: gjhe@hku.hk). Pan: Institute for Global Health and Development and Institute of Carbon Neutrality, Peking University (email: yhpan@pku.edu.cn). Xie: Department of Economics, University of California, Riverside (email: yang.xie@ucr.edu). We thank Stefan Ambec, Ujjayant Chakravorty, Kim Sau Chung, Lawrence Goulder, Joshua Graff Zivin, Michael Greenstone, Andrew Hultgren, Valerie Karplus, Koichiro Ito, Mark Jacobsen, Ryan Kellogg, Matthew J. Kotchen, Shanjun Li, Sarah Miller, Nick Muller, David A. Raitzer, José Scheinkman, Jay Shimshack, Ulrich Wagner, Shaoda Wang, Daniel Yi Xu, Andrew Yates, seminar participants at the Asian Development Bank, Chinese University of Hong Kong, Fudan University, Hong Kong University of Science and Technology, National University of Singapore, Peking University, Renmin University, Shanghai University of Finance and Economics, Stanford University, University of Hong Kong, Xiamen University, and participants at the 2022 ASSA Meeting, 2023 AERE Summer Conference, EPIC Conference on Counting the Costs and Addressing the Impacts of Climate Change, and the 4th Forum for China's Energy, Environment and Climate Change Economics for their valuable comments. We appreciate the financial support from the Hong Kong Research Grant Council (GRF 17503022).

I. Introduction

One fundamental question in economics is to compare economic coordination by planning versus the market, i.e., whether "the use of knowledge in society" is centralized or not (Arrow 1951; Debreu 1951; Hayek 1945; Lange 1942; von Mises 1935). When it comes to achieving a pre-determined target of emission abatement, the market approach would be to use a market for tradable emission permits, which, by itself, does not involve any centralized processing of information, whereas the planning approaches would require the policymaker to do so, including, 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, 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. This setting is important because our results can inform other policy design contexts where both incomplete information and local externalities are common. In particular, we focus on a general context in which the policy designer needs to achieve a pre-determined collective target of abatement, and we 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 the market approach can solve the problem of incomplete information but not the problem brought by heterogeneous local externalities of abatement, whereas the opposite is true for the planning approach. Therefore, as the policymaker tries to achieve a pre-determined collective target of abatement more efficiently, the market will help her more if and only if the concern of incomplete information is more serious than the concern of heterogeneous 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 its tradition from 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

[1] When incomplete information is present, other slightly more complicated policy instruments, such as assigning heterogeneous trading ratios in emission trading, cannot guarantee to achieve a pre-determined collective target. This is because, when the trading ratios differ across sources, the sum of emissions will vary according to the realized values of abatement costs (Holland and Yates, 2005). See Appendix A for details. 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 ambitious, especially considering that the country's carbon emissions are still rising (United Nations Environment Programme 2021).

power-generation sector has eventually been established since 2021, after a decade of 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 (United Nations Development Programme 2019; Greenstone et al. 2021), 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 2021. 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 more cases of corruption investigations, poorer environmental governance records, and high levels of local R&D expenditures.

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 2021, 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

[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.

in each locality. Our calculation shows that there exists substantial heterogeneity in local 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 heterogeneous 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 smaller than the welfare loss caused by failing to address heterogeneous local externalities under a national carbon market. The planning-alone approach is thus more efficient than the market-alone approach in achieving a pre-determined target of carbon abatement in China.

This is not to say that a national abatement plan 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 another 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 heterogeneous local externalities, which often arise from heterogeneous local damages of emissions, and policy augmentations, such as heterogeneous trading ratios, have been proposed (Montgomery 1972; Tietenberg 1980, 1995; Klaassen et al. 1994; Farrow et al. 2005; Muller and Mendelsohn 2009; Henry et al. 2011; Kuwayama and Brozović 2013).

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) show that, in an allowance market with heterogeneous trading ratios, incomplete information about the abatement cost makes the total emission stochastic and thus impossible to fully control ex ante; Fowlie and Muller (2019) analyze how this incomplete information complicates differentiated policy solutions to heterogeneous local externalities; nevertheless, the trade-off itself is still not in the focus.

We analyze this trade-off given an exogenous collective target of abatement. This is an important setting to analyze because, first, it fits to the real-world policy situations where a pre-determined collective target has been specified.[4] Second, it allows us to characterize the main trade-off between the market approach and the planning approach in one

[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.

integrated framework, to show that this trade-off hinges on the relative significance of the information problem and the externality problem, and 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, not focusing on incomplete information and local externalities, Goulder et al. (2022, 2026) and Wang et al. (2022) assess the welfare implications of China's Tradable Performance Standard (TPS) instrument. 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 (Banzhaf et al. 2019; Bento 2013; Hsiang et al. 2019; Jensen et al. 2015; Krusell and Smith 2022; Schmalensee and Stavins 2013; Conte et al. 2025).

At a more conceptual level, economics has a prominent tradition in comparing economic coordination by the 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 a quantity signal versus planning by a price signal, with applications primarily in environmental economics; the most recent contributions to this area are not limited to Karp and Traeger (2024), Mideksa and Weitzman (2019), and Schlee (2025). 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 heterogeneous 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 since Q is exogenous, they are not a concern here.

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

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

Assuming interior solution, the first-order condition is

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

where $q_1^*,\dots,q_N^*$ 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 B. 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 the 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:

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

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*

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

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

The proof is in Appendix C. 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 $\theta_1,\dots,\theta_N$. 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. The second point here 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. The first point is not in his focus, though: he is comparing two planning schemes, i.e., using the price vs. the quantity signal, so he has to take the magnitude of incomplete information as given.

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

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

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 D, 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*

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

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

The proof is in Appendix E. The main step is to recognize the law of one price in the market of abatement targets, 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. The second point is consistent with the classic insight of Weitzman (1974). By contrast, the role of local externalities, which is captured in the first point here, is not present in his framework.

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

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

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

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

The proof is in Appendix F, 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_is 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*

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

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

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 heterogeneous local externalities solved. The market approach addresses the incomplete information problem while missing heterogeneous 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, it is natural to ask: 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, 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

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

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

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

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 $a = 0, \dots, A$*,*

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

$$\bar{x}^a \equiv \sum_{i \in I^a} \widetilde{w}_i \, x_i, \;\; D_x^a \equiv \sum_{i \in I^a} \widetilde{w}_i \, (x_i - \bar{x}^a)^2;$$

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 G. 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 market approach 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 planning approach 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 heterogeneous 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, but 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. That said, because there existed significant production leakages within the large conglomerates, the program was not successful (Chen et al. 2025). 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 to 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 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).

[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%.

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 trade carbon allowances. Instead, it is a Tradable Performance Standard (TPS) instrument that targets emission intensity. In this paper, we choose to focus on the classic CAT-type market, 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

[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 2023).

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 contributions of (Goulder et al. 2022, 2026).[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.

That being said, in appendix H, we provide a theoretical bound of the potential welfare improvement from the TPS instrument relative to the CAT-type market, provided that we focus on the welfare implications that arise from the total cost and local externalities of abatement. Based on this theoretical bound, we also conduct a brief numerical analysis about the TPS instrument in the Chinese context; we discuss the results in Section IV.

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

[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.

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 et al. 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 equivalent 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 2021. 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 2021.[9] Because air quality can be affected by weather conditions, we also collect meteorological data, including temperature and precipitation, from the Global Historical Climatology Network of the U.S. National Oceanic and Atmospheric Administration.

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 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 CO_2 emissions are outputs, and then, by predicting

[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.

the substitution rate between them on the estimated frontier (Färe et al. 1993, 2005; Chung et al. 1997). Appendix H 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 2012 to 2021. We utilize the policy change in 2011 to construct the counterfactuals. Recall that in December 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-CO_2 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 emissions abated in each year.

In the third step, for each province, we combine the MAC and abatement estimates after 2012 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 $n = 10$ 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.

2. Results

Figure 4 illustrates the process of estimating the marginal abatement cost curve using data from Hebei 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 since 2012. The predicted counterfactual emissions are represented by the red line,

[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.

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 Inner Mongolia, Liaoning, and Ningxia, implying potential gain from carbon trading among these provinces in solving the informational problem. In 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 (2012–2021), the number of environmental penalty cases, and the local R&D expenditures. Collectively, these three figures show that incomplete information tends to be more severe in provinces characterized by a larger number of corruption investigations, a higher volume of environmental penalty cases, and higher levels of R&D expenditures.

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 begin by documenting the empirical relationship between carbon emissions and multiple dimensions of air pollution. Figure S3 presents cross-sectional evidence at the

provincial level. Panel A shows that carbon emissions are positively correlated with ambient air quality, as measured by the Air Quality Index (AQI), with provinces exhibiting higher carbon emissions tending to experience worse air quality.[11] Panels B–D further show that carbon emissions are strongly and positively correlated with emissions of major air pollutants, including industrial dust, SO_2, and NO_x. These relationships are approximately linear and quantitatively substantial, indicating that provinces with higher carbon emissions systematically emit larger quantities of conventional air pollutants.

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

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

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.

Columns (1) to (7) in Table S2 report the regression results across seven ambient air quality indicators, including the AQI, $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and Ozone. We find a robust positive association between carbon emissions and air pollution. In particular, a 1% increase in carbon emissions is associated with a 0.28% increase in AQI and a 0.28-0.39% increase in particulate matter concentrations ($PM_{2.5}$ and PM_{10}), both statistically significant at the 1% level. The estimated relationships with gaseous pollutants — including SO_2, NO_2, CO, and Ozone — are weaker in magnitude and less precisely estimated. This pattern suggests that the relationship between carbon emissions and air pollution mainly operates through particulate matter, rather than gaseous pollutants. In Panel (8) of Table S2, we also summarize the regression results for industrial dust emissions. We find that a 1% increase in carbon emission is associated with a 0.49% increase in industrial dust emissions.

[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.

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. (2026)'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 I. Consistent with the empirical patterns above—where the association between carbon emissions and air pollution is more salient for AQI and particulate matter—we base our monetization on particulate exposure and AQI levels, following the existing literature, which typically focuses on a limited set of pollutants (for example, $PM_{2.5}$ or PM_{10}).[14] As a result, the impacts of other air pollutants (like SO_2, NO_x, CO, and Ozone) are not fully captured in our estimates.

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:

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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 SO_2, NO_x, or other pollutants.

$$LocalEC_i = pop_{i,2021} * \hat{\gamma}_i * \sum_j \hat{a}_j, \quad (7)$$

where pop_i indicates the population in province i in 2021; $\hat{\gamma}_i$ 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 2021; $\hat{a}_j$s are the estimated health and economic costs of per unit change in air pollution for outcome j, i.e., mortality costs, morbidity costs, productivity loss, or defensive expenditures.

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. Planning

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 national planning is more efficient in achieving a given collective target of carbon abatement

because the expected welfare loss under the planning (16.35 billion USD/Year) is smaller than the expected welfare loss under market (24.83 billion USD/Year). In Appendix K, we bootstrap the distributions of the estimates of ΔW^{Market} and ΔW^{Plan}. Figures S6 and S7 and the Kolmogorov–Smirnov test in Table S4 suggest that the distribution of the estimate of ΔW^{Plan} indeed contains generally smaller values than the distribution of the estimate of ΔW^{Market}.

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.

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 7.

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). Considering 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.

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 abatement technology in certain firms/industries than others. Among these regions, 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 the 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, following 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 heterogeneous 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 13, 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. For example, as shown in the figure, if we have about 15 provinces in carbon trading, having two markets dominates having only one, or four, ten, or 15 separate markets.

Quantitatively, hybrid schemes can substantially reduce expected welfare losses. As an illustration, assigning 13 provinces to a subnational carbon market and the remaining 17 provinces to a planning regime yields an expected welfare loss of 8.43 billion USD per year — 66.0% lower than the national market benchmark and 48.4% lower than the national planning benchmark. Further gains can be achieved by introducing multiple subnational markets. As shown by the solid green-teal line in Figure 9, the welfare loss is minimized when two provinces are assigned to the planning regime, and the remaining 28 provinces are allocated across four subnational markets. In this case, the expected welfare loss declines to 2.95 billion USD per year, representing reductions of 82.0% and 88.1% relative to the national planning and market benchmarks, respectively.[15]

Welfare implications of the TPS instrument and potential of the hybrid schemes. As discussed in Section III, we have provided in Appendix H a theoretical upper bound of the potential welfare improvement from the TPS instrument relative to the CAT-type market-alone approach, focusing only on the welfare implications that arise from the total cost and local externalities of abatement. In Appendix Figure S8, we compare this upper bound with the welfare improvement from the best hybrid scheme in our illustration above, which consists of a two-province subnational plan and four seven-province

[15] Figure S5 in Appendix plots the lowest expected welfare losses the hybrid schemes in our simulation can achieve across the number of subnational markets used in scheme. The lowest is indeed achieved when it has four subnational markets.

subnational markets, both relative to a national CAT-type market. As the figure shows, if the collective target of abatement is set at the 2012–2021 annual average the total abatement among the 30 Chinese provinces, even the upper bound of the potential welfare improvement from the TPS instrument is still lower than the potential welfare improvement from the best hybrid scheme in our illustration above. At the same time, Goulder et al. (2022) reports that, in the Chinese context, the TPS instrument would induce a worse welfare outcome in the energy output market, where the CAT-type market-alone approach and our hybrid scheme would not create any welfare loss in theory. All this implies that, in the Chinese context, when considering their potential welfare improvement relative to a national CAT-type market, respectively, one may need to be cautious about the TPS instrument, but can be more optimistic about a well-designed hybrid scheme.

Interactive Welfare Calculator. All welfare comparisons above depend on a small set of key parameters. Consequently, variations in these parameters mechanically translate into differences in the relative performance of different schemes. To facilitate transparent evaluation under alternative parameter configurations, we provide an interactive welfare calculator at china-carbon-market.netlify.app. The website allows the users to specify the values of the key parameters in our model – the slopes of marginal abatement costs, heterogeneity of local externalities, and levels of incomplete information – and compute the corresponding welfare outcomes under planning, cap-and-trade, and hybrid schemes.

VII. Conclusion

This paper compares the welfare consequences of the market and planning approaches to achieving a pre-determined collective target of emission abatement, taking into account both incomplete information about abatement costs and local externalities of abatement. We show that the comparison depends on the relative importance of the informational problem and the heterogeneity in local externalities, and we derive a simple sufficient statistic for this trade-off, a rule of thumb for policy choice, and a formula to

estimate the expected welfare loss of hybrid schemes that combine the planning and market approaches.

We illustrate the theoretical results by applying them to the debate over China's strategy for reducing carbon emissions. In this empirical context, we find that the expected welfare loss under a carbon market can exceed that under planning, owing to substantial heterogeneity in the local externalities of carbon abatement across China. We further discuss alternative policies that may improve social welfare, including a national carbon market combined with locality-specific abatement subsidies, and hybrid schemes consisting of a subnational abatement plan and a limited number of subnational carbon markets. We show that these alternatives – particularly the hybrid schemes when locality-specific subsidies are not feasible – can significantly improve welfare relative to both the national planning and market benchmarks, and therefore warrant further exploration.

Our results have several policy implications. First, although many countries have established, planned, or proposed carbon markets to mitigate climate risks, policy discussions have focused primarily on their cost-saving benefits, with less attention to their limitations. Our analysis highlights, both theoretically and empirically, the importance of heterogeneous local externalities in evaluating the welfare consequences of carbon trading, and thus in improving the design and operation of carbon markets. Second, we provide a rule of thumb for policy choice. For countries facing severe informational frictions and relatively limited regional heterogeneity in population and income, carbon markets are likely to be more attractive. By contrast, when information about production technology is relatively complete, or when regions differ substantially in pollution exposure, income, and population, planning may be the better option. Finally, because carbon emissions and air pollution are highly correlated, policymakers should adopt a more integrated approach to climate policy and pollution regulation. Our analysis suggests that treating these policy domains separately can generate substantial welfare losses.

We conclude by noting several caveats. First, while we carefully estimate the model parameters using Chinese data, the empirical exercise is primarily illustrative. Each step of the parameterization requires assumptions and subjective choices, including how to

estimate marginal abatement cost curves and their uncertainty, which dimensions and time horizons of local externalities to emphasize, how to transfer estimates of pollution damages, and how to monetize non-market goods such as human life. Different choices could lead to different quantitative results. Second, we abstract away from firm entry and exit and from the movement of individuals across regions, both of which may have important welfare consequences. Third, our empirical analysis is conducted at the provincial level and focuses on allocating a national target across provinces; more disaggregated target allocation within provinces, prefectures, or counties would require different data and could imply different welfare and policy conclusions. Finally, carbon abatement may also have heterogeneous local benefits through the spatially uneven effects of global warming itself, a channel we do not incorporate in our welfare calculations. We leave these richer settings for future research. Nonetheless, together with the interactive welfare calculator introduced in Section VI, our framework provides a practical way to evaluate the welfare implications of planning, market, and hybrid policies under alternative parameter values.

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Tables and Figures

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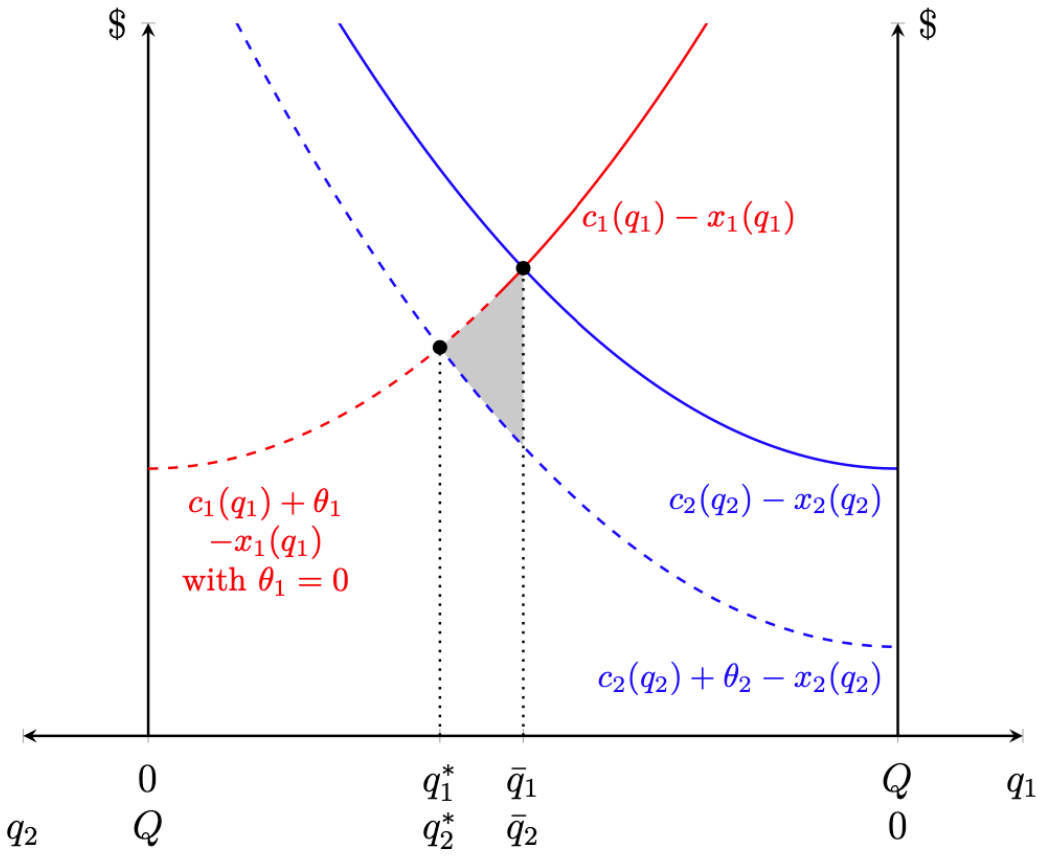


Figure 1. Welfare Implications under Planning

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.

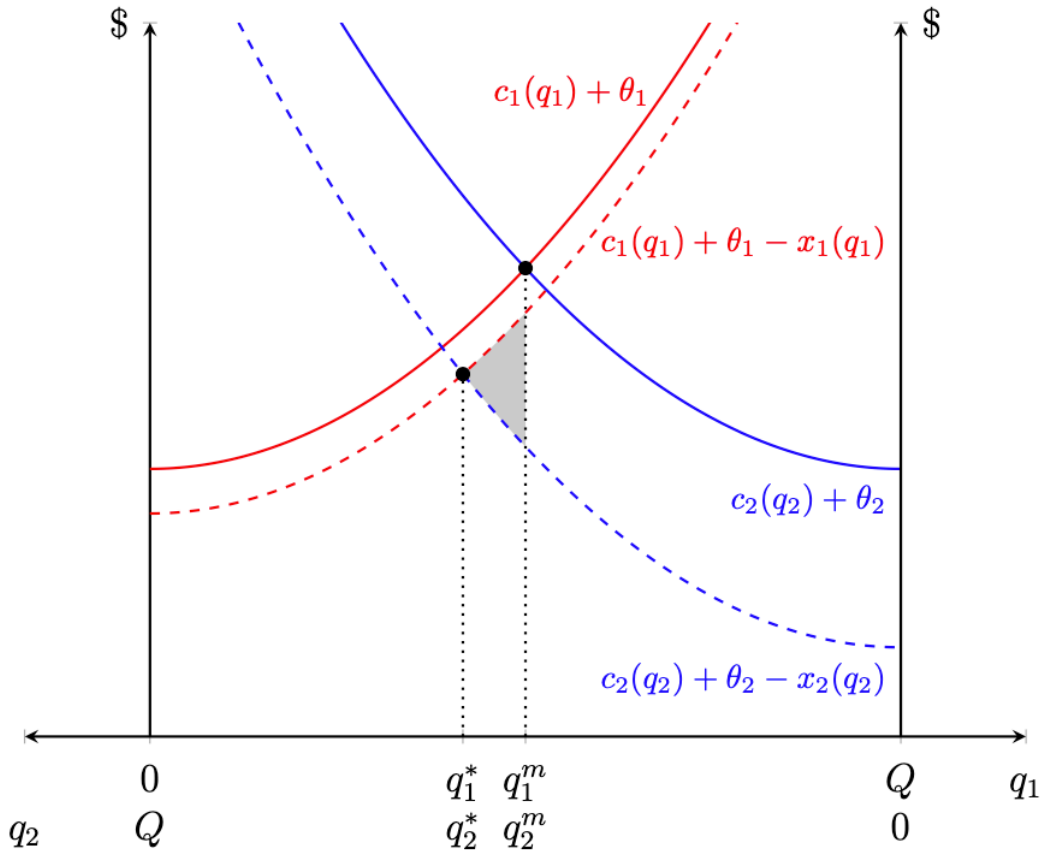


Figure 2. Welfare Implications under Market

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.

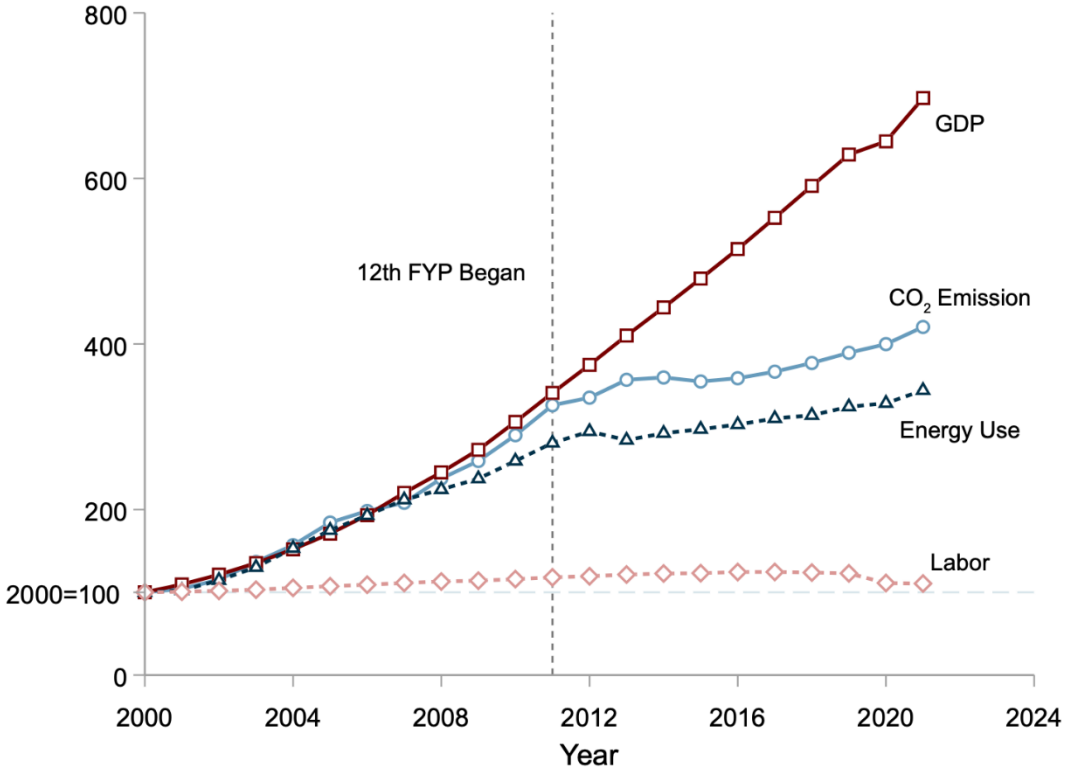


Figure 3. CO_2 Emissions, Energy Use, GDP, and Labor in China

Notes: This figure shows China's GDP, carbon emissions, energy consumption, and labor from 2000 to 2021, 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).

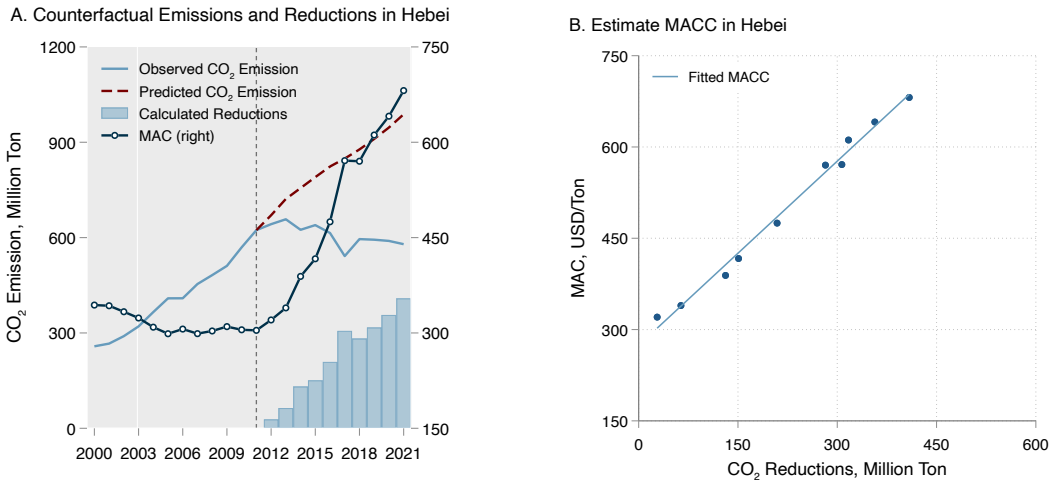


Figure 4. Estimate Marginal Abatement Cost Curve: An Example

Notes: This figure illustrates how to estimate the marginal abatement cost curve using data from Hebei 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 2021, 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 2021. 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).

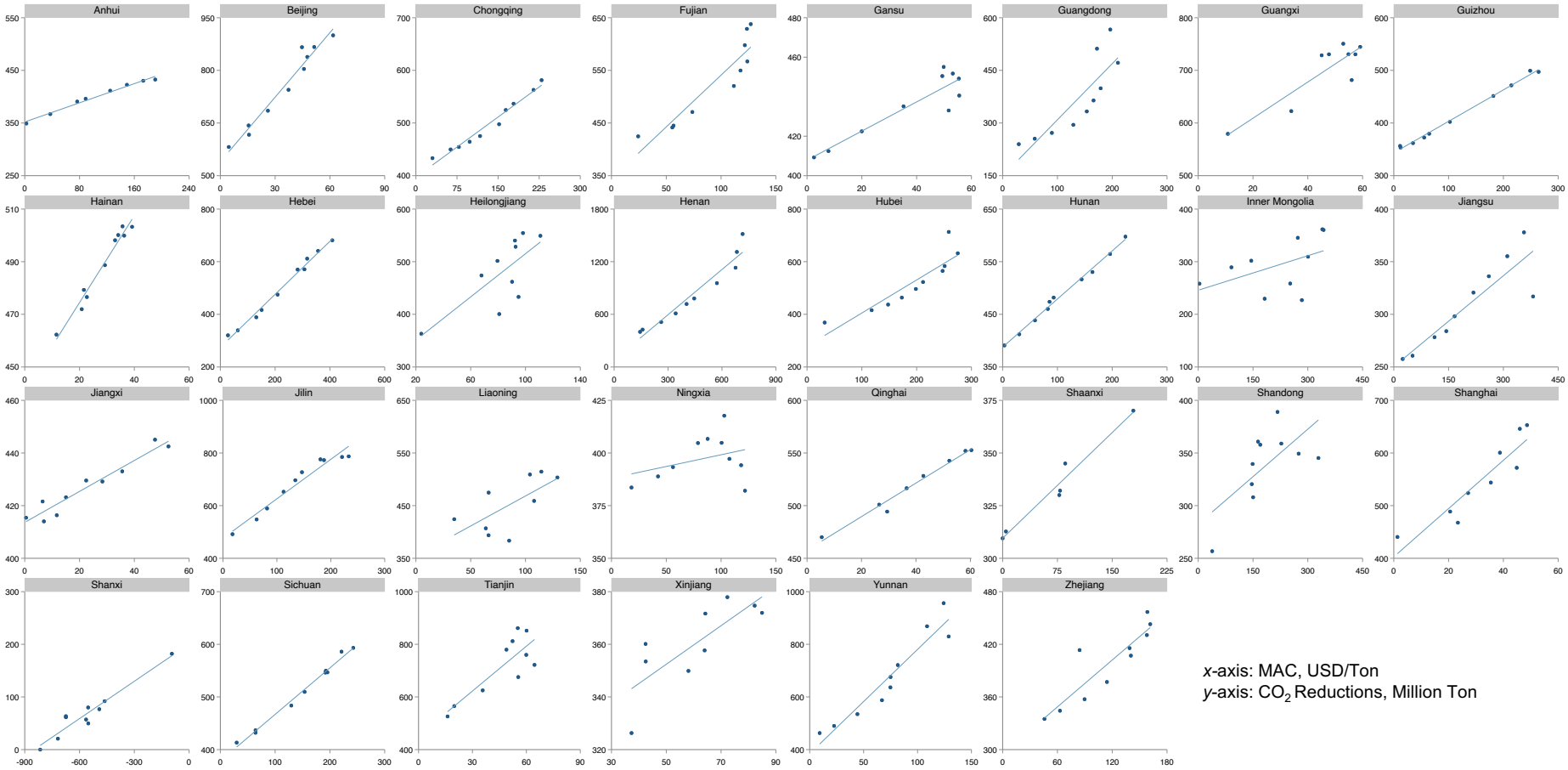
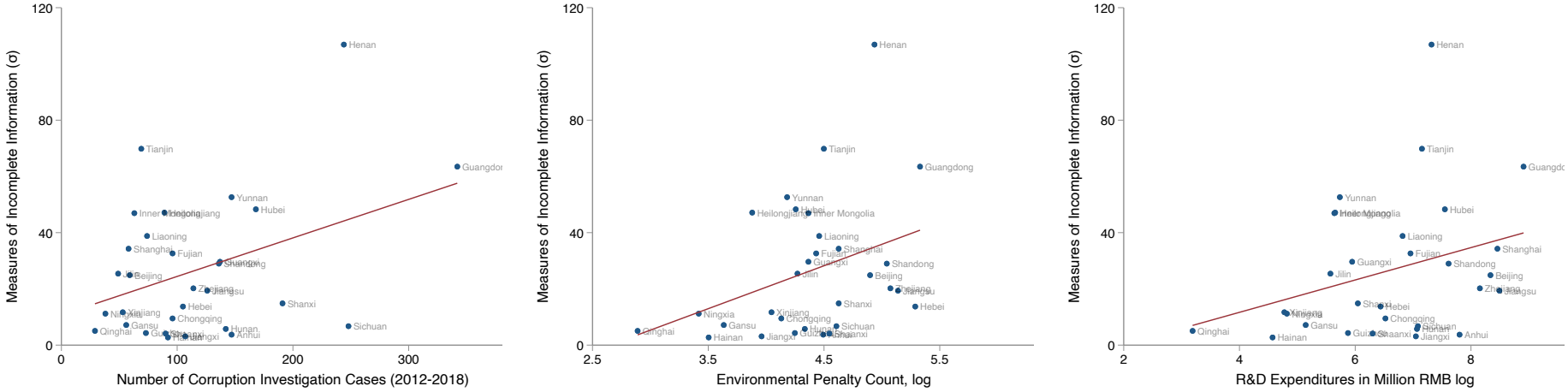


Figure 5. Fitted Marginal Abatement Cost Curves for 30 Provinces

Notes: This figure summarizes the estimated marginal abatement cost curves for 30 provinces for 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.



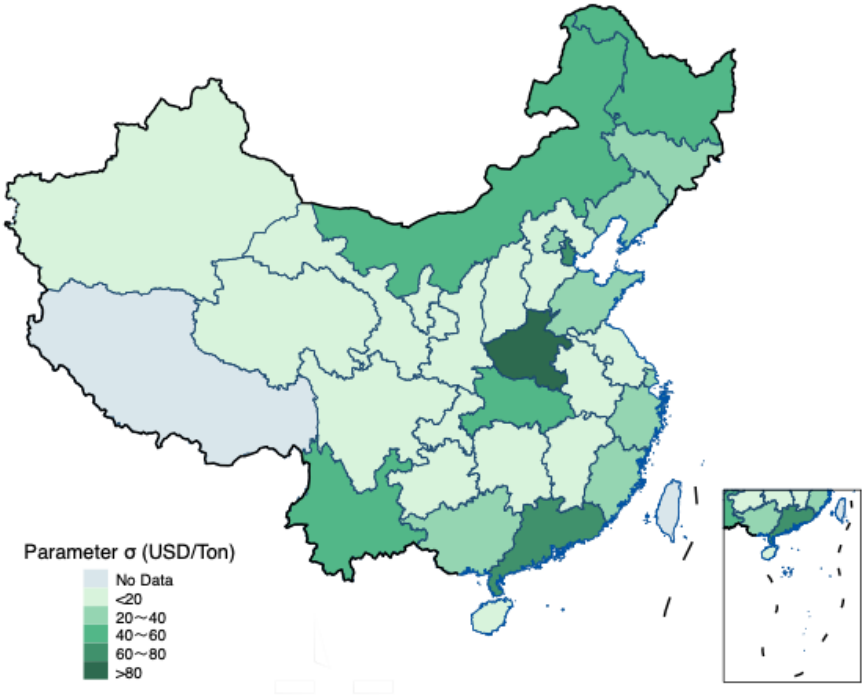
A. Incomplete Information and the Number of Corruption Investigations

B. Incomplete Information and the Number of Environmental Penalty Cases

C. Incomplete Information and Local R&D Expenditures

Figure 6. Incomplete Information and Local Characteristics

Panel A. Measuring Incomplete Information about MACC in Chinese Provinces



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

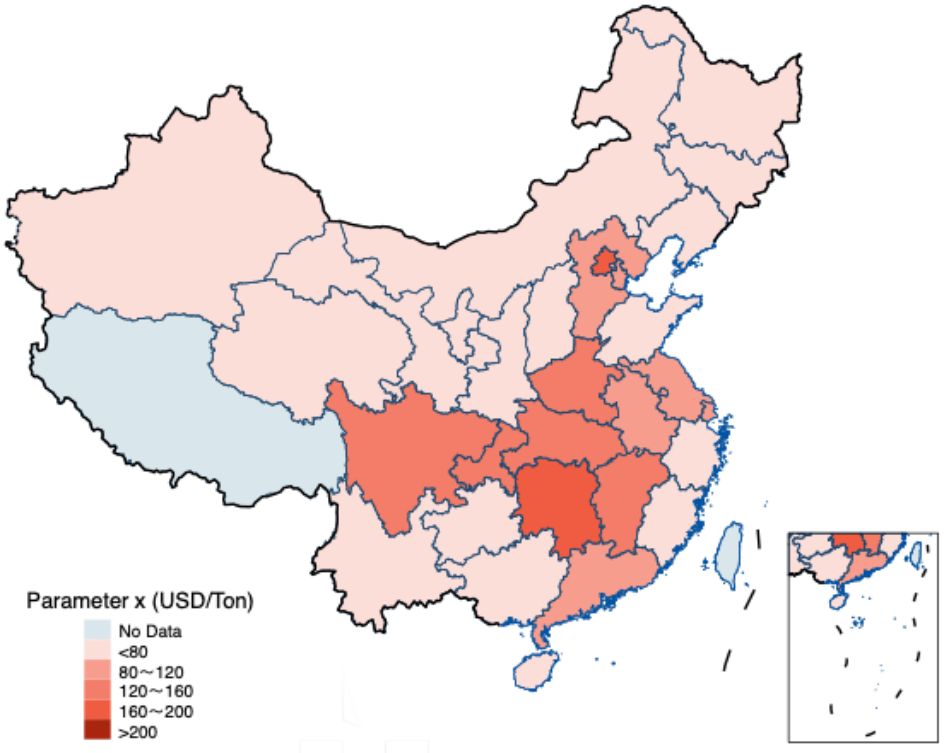


Figure 7. Significance of Information Incompleteness and Heterogeneity in Local Externalities of Carbon Abatement

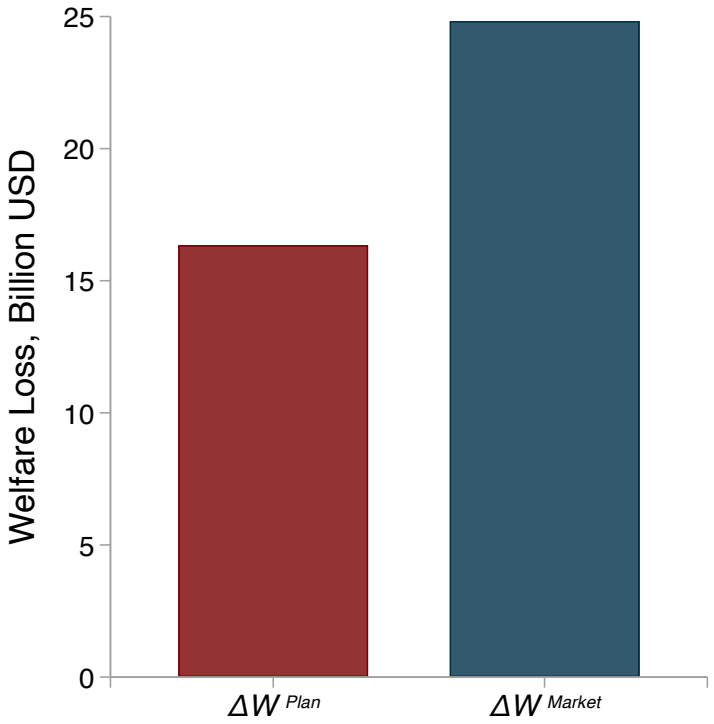


Figure 8. Compare Expected Welfare Losses between Market and Planning

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.

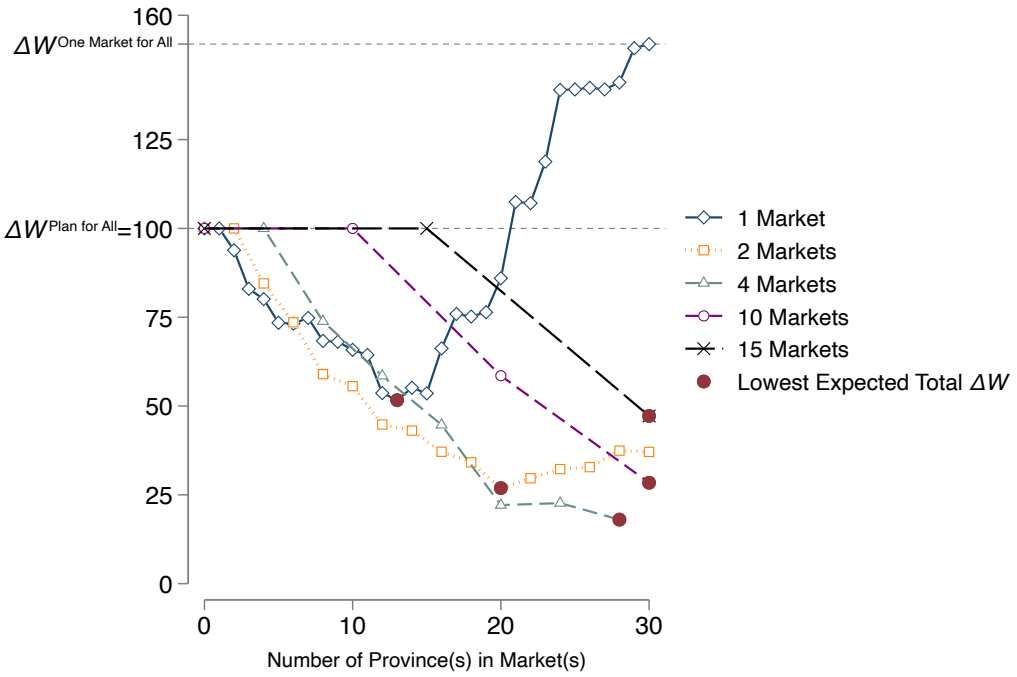


Figure 9. Expected Welfare Losses under Hybrid Schemes

Note: In each hybrid scheme, we first rank the 30 Chinese provinces 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., heterogeneous marginal local externalities	Be careful, especially with high S, i.e., flat marginal costs	Plan

Table 2. 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. (2026)
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"

Guojun He Yuhang Pan Yang Xie

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Appendix A. Market with Potentially Heterogeneous Trading Ratios

Following the theoretical setting and notations in the main text, now consider a market for abatement targets where, for each firm i, one unit of its real abatement will fulfill $r_i > 0$ units of abatement targets. Following the convention in the literature (e.g., Holland and Yates, 2015), we call $r_1, \dots, r_N$ the trading ratios.

In this scheme, firm i is still to maximize the profit from target trading, net of its abatement cost, by choosing its abatement q_i, but the program would become

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

where p^m is still the price for one unit of abatement target and $\widetilde{q_i}$ is still the initial allocation of targets. Assuming interior solution, the first-order condition is

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

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

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

Observe from this condition that, for any given trading ratios $r_1, \dots, r_N$, the market-equilibrium abatements $q_1^m, \dots, q_N^m$ would depend on not only $r_1, \dots, r_N$, but also $\theta_1, \dots, \theta_N$, which are unknown to the policy designer ex ante. Note that the policy instruments the policy designer controls include only the trading ratios $r_1, \dots, r_N$ and the initially issued targets $\tilde{q}_1, \dots \tilde{q}_N$. Therefore, the policy designer generally cannot control the market-equilibrium abatements $q_1^m, \dots, q_N^m$. Moreover, only by setting $r_i = r_j \equiv r$ for any $i, j = 1, \dots, N$, she would be able to control the market equilibrium, $\sum_{i=1}^N q_i^m$, since

$$\sum_{i=1}^{N} r_i \tilde{q}_i = \sum_{i=1}^{N} r_i q_i^m = \sum_{i=1}^{N} r q_i^m = r \cdot \sum_{i=1}^{N} q_i^m,$$

i.e.,

$$\sum_{i=1}^{N} q_i^m = \sum_{i=1}^{N} r_i \tilde{q}_i = r \cdot \sum_{i=1}^{N} \tilde{q}_i ;$$

without setting $r_i = r_j$ for any $i, j = 1, \dots, N$, the policy designer would not be able to control $\sum_{i=1}^N q_i^m$. The same argument runs in Holland and Yates (2015, p. 19): "[i]n general, …when the trading ratios differ between sources, the sum of emissions will not be constant, and moreover, it will vary according to the realized values of Θ," i.e., the parameters in the abatement cost functions that are incomplete information to the policy designer.

Therefore, to achieve the exact collective target Q ex post, the policy designer must use homogeneous trading ratios, i.e., setting $r_i = r_j \equiv r$ for any $i, j = 1, \dots, N$. This would reduce the policy designer's problem into the market scheme we have analyzed.

For a problem where the policy designer is allowed to breach the collective abatement target Q, see the analysis by Holland and Yates (2015) on the optimal trading ratios in expectation.

Appendix B. 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

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

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 C. 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

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

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

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

Appendix D. 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

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

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

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

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

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

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

$$
\begin{aligned}
&(\bar{q}_i - q_i^*)^2 \\
&\approx \left(\frac{\dfrac{Q - \sum_{i=1}^{N} \dfrac{x_i - c_i(0)}{c'_i}}{\sum_{i=1}^{N} \dfrac{1}{c'_i}} + x_i - c_i(0)}{c'_i} - \frac{\dfrac{Q - \sum_{i=1}^{N} \dfrac{x_i - c_i(0) - \theta_i}{c'_i}}{\sum_{i=1}^{N} \dfrac{1}{c'_i}} + x_i - c_i(0) - \theta_i}{c'_i} \right)^2 \\
&= \left(\frac{\theta_i - \dfrac{\sum_{i=1}^{N} \dfrac{\theta_i}{c'_i}}{\sum_{i=1}^{N} \dfrac{1}{c'_i}}}{c'_i} \right)^2 = \frac{\left(\theta_i - \dfrac{\sum_{i=1}^{N} \dfrac{\theta_i}{c'_i}}{\sum_{i=1}^{N} \dfrac{1}{c'_i}} \right)^2}{{c'_i}^2}.
\end{aligned}
$$

Taking it with the first approximation, we can thus approximate

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

where

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

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

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

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

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

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 E. 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 F. 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

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

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

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

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

$$\begin{aligned}
&(q_i^m - q_i^*)^2 \\
&\approx \left(\frac{\frac{Q - \sum_{i=1}^N \frac{-c_i(0) - \theta_i}{c'_i}}{\sum_{i=1}^N \frac{1}{c'_i}} - c_i(0) - \theta_i}{c'_i} - \frac{\frac{Q - \sum_{i=1}^N \frac{x_i - c_i(0) - \theta_i}{c'_i}}{\sum_{i=1}^N \frac{1}{c'_i}} + x_i - c_i(0) - \theta_i}{c'_i} \right)^2 \\
&= \left(-\frac{x_i - \frac{\sum_{i=1}^N \frac{x_i}{c'_i}}{\sum_{i=1}^N \frac{1}{c'_i}}}{c'_i} \right)^2 = \frac{\left(x_i - \frac{\sum_{i=1}^N \frac{x_i}{c'_i}}{\sum_{i=1}^N \frac{1}{c'_i}} \right)^2}{{c'_i}^2}.
\end{aligned}$$

Taking it with the first approximation, we can thus approximate

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

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 G. 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

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

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

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

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

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

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

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

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 $a = 1, \ldots, A$, 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

$$\begin{aligned}
&(q_i^m - q_i^*)^2 \\
&\approx \left(\frac{\bar{Q}^a - \sum_{i\in I^a} \frac{-c_i(0) - \theta_i}{c'_i}}{\sum_{i\in I^a} \frac{1}{c'_i}} - c_i(0) - \theta_i \right. \\
&\qquad \left. \frac{}{c'_i} - \frac{Q^{*a} - \sum_{i\in I^a} \frac{x_i - c_i(0) - \theta_i}{c'_i}}{\sum_{i\in I^a} \frac{1}{c'_i}} + x_i - c_i(0) - \theta_i \right)^2 \\
&\qquad \frac{}{c'_i} \\
&= \left(x_i - \frac{\sum_{i\in I^a} \frac{x_i}{c'_i}}{\sum_{i\in I^a} \frac{1}{c'_i}} - \frac{\bar{Q}^a - Q^{*a}}{\sum_{i\in I^a} \frac{1}{c'_i}} \right)^2 = \frac{\left(x_i - \bar{x}^a - \frac{\bar{Q}^a - Q^{*a}}{\sum_{i\in I^a} \frac{1}{c'_i}} \right)^2}{{c'_i}^2},
\end{aligned}$$

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 $a = 0, \dots, A$. 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 $Q = \sum_{i \in I} q_i^*$, 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

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

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 $a = 1, \dots, A$, 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 $a \in 1, \dots, A$,

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

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

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

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

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

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 $\bar{x}^a$,

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

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

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

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

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

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

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

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

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

where

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

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

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

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

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

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

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

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

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

$$\approx \frac{1}{2}\cdot\left(\sum_{i\in I^0}\mathbf{E}\left[c'_i\cdot\frac{(\theta_i-\bar{\theta}^0+\bar{\theta}^0-\bar{\theta})^2}{{c'_i}^2}\right]+\sum_{a=1}^{A}\left(\sum_{i\in I^a}\mathbf{E}\left[c'_i\cdot\frac{(x_i-\bar{x}^a-\bar{\theta}^a+\bar{\theta})^2}{{c'_i}^2}\right]\right)\right)$$

$$=\frac{1}{2}\cdot\left(\sum_{i\in I^0}\mathbf{E}\left[\frac{(\theta_i-\bar{\theta}^0+\bar{\theta}^0-\bar{\theta})^2}{c'_i}\right]+\sum_{a=1}^{A}\left(\sum_{i\in I^a}\mathbf{E}\left[\frac{(x_i-\bar{x}^a-\bar{\theta}^a+\bar{\theta})^2}{c'_i}\right]\right)\right)$$

$$=\frac{1}{2}\cdot\left(\sum_{i\in I^0}\left(\frac{1}{c'_i}\cdot\mathbf{E}[(\theta_i-\bar{\theta}^0+\bar{\theta}^0-\bar{\theta})^2]\right)+\sum_{a=1}^{A}\left(\sum_{i\in I^a}\left(\frac{1}{c'_i}\cdot\mathbf{E}[(x_i-\bar{x}^a-\bar{\theta}^a+\bar{\theta})^2]\right)\right)\right).$$

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

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

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

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

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

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

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

for $i \in I^a$, where $a = 1, \ldots, A$, 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

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

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 $a = 0, \ldots, A$,

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

$$\equiv \sum_{i\in I^a}\widetilde{w}_i\,(x_i - \bar{x}^a)^2;$$

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

The proposition is thus proved.

Appendix H. Tradable Performance Standard

In this section we explore how a tradeable-performance-standard (TPS) instrument would differ from the regular market scheme as we have analyzed.

To set up the analysis, first, denote firm i's output as $y_i \geq 0$ and emission as $e_i \geq 0$. In particular, denote firm i's business-as-usual output as $\bar{y}_i$ and business-as-usual emission as $\bar{e}_i$. Still denote the firm's emission abatement, now specifically with respect to the business-as-usual level, as $q_i \equiv \bar{e}_i - e_i$.

Second, assume that each firm is subject to a given productive technology, characterized by the marginal cost of output, $\kappa_i(y_i)$, where $\kappa_i'(y_i) > 0$, and the business-as-usual efficiency, $\bar{\beta}_i$, such that, for each unit of output, it generates $\bar{\beta}_i y_i$ units of emission. In particular, in the business-as-usual scenario, $\bar{e}_i = \bar{\beta}_i \bar{y}_i$.

Third, assume that each firm is subject to a given abatement technology, still characterized by the marginal cost of abatement, $c_i(q_i) + \theta_i$. The policy designer still has incomplete information about and only about θ_i, with $\boldsymbol{E}[\theta_i] = 0$, $\boldsymbol{E}[\theta_i^2] = \sigma_i^2$, and mutual independence among all θ_is. Still denote the marginal local externality of abatement as $x(q_i)$.

(1) Regular Market Scheme

Under the regular market scheme, first, each firm still receives an exogenous initial allocation of abatement targets, $\tilde{q}_i$, such that $\sum_{i=1}^{N} \tilde{q}_i = Q$, where $Q > 0$ is still the exogenous collective abatement target. Each firm then decides its output y_i and abatement q_i, while trading the abatement targets in a market as a price taker, and selling the output in the output market at an exogenous, potentially firm-specific price π_i. Still denote the market price of the abatement target as p^m and the market-equilibrium allocation of abatement as q_i^m; denote the market-equilibrium output as y_i^m.

Lemma 5. *Under the regular market scheme, assuming interior solutions, the equilibrium outputs and abatements satisfy* $p^m = c_i(q_i^m) + \theta_i = c_j(q_j^m) + \theta_j$, for any $i, j = 1, \dots, N$; $\pi_i = \kappa_i(y_i^m)$, for any $i = 1, \dots, N$; $\sum_{i=1}^{N} q_i^m = Q$.

Proof. Under this scheme, each firm's program is

$$\max_{q_i, y_i} \quad \pi_i y_i - \int_0^{y_i} \kappa_i(y)dy + p^m(q_i - \tilde{q_i}) - \int_0^{q_i} (c_i(q) + \theta_i)\, dq, \quad \text{s.t.}$$

$$q_i \geq 0, \quad y_i \geq 0.$$

Assuming interior solutions, the first-order conditions are

$$p^m = c_i(q_i^m) + \theta_i, \quad \pi_i = \kappa_i(y_i^m).$$

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

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

By the clearance of the market of abatement targets, we still have

$$\sum_{i=1}^{N} q_i^m = \sum_{i=1}^{N} \tilde{q}_i = Q.$$

The equilibrium conditions are then as described.

(2) TPS Scheme

Under the TPS scheme, the policy designer announces potentially firm-specific benchmark efficiencies, $\check{\beta}_1, \dots, \check{\beta}_N$. Given these benchmark efficiencies, each firm decides its output y_i and abatement q_i, while receiving an endogenous initial allocation of abatement targets

$$\check{q}_i = \bar{e}_i - \check{\beta}_i y_i,$$

trading the abatement targets in a market as a price taker, and selling the output in the output market at the same exogenous, potentially firm-specific price π_i. Denote the market price for the abatement target as p^{TPS}, the market-equilibrium allocation of abatement as

q_i^{TPS}, the market-equilibrium output as y_i^{TPS}, and the market-equilibrium initial allocation of abatement targets as $\breve{q}_i^{TPS}$.

Lemma 6. *Under the TPS scheme, assuming interior solutions, the equilibrium outputs and abatements satisfy* $p^{TPS} = c_i(q_i^{TPS}) + \theta_i = c_j(q_j^{TPS}) + \theta_j$, for any $i, j = 1, \dots, N$; $\pi_i + p^{TPS}\breve{\beta}_i = \kappa_i(y_i^{TPS})$, for any $i = 1, \dots, N$; $Q^{TPS} \equiv \sum_{i=1}^{N} q_i^{TPS} = \sum_{i=1}^{N}(\bar{e}_i - \breve{\beta}_i y_i^{TPS})$.

Proof. Under this scheme, each firm's program is

$$\max_{q_i, y_i} \quad \pi_i y_i - \int_0^{y_i} \kappa_i(y)dy + p^{TPS}(q_i - \breve{q}_i) - \int_0^{q_i} (c_i(q) + \theta_i)\, dq, \quad \text{s.t.}$$

$$q_i \geq 0, \quad y_i \geq 0, \quad \breve{q}_i = \bar{e}_i - \breve{\beta}_i y_i.$$

Assuming interior solution, the first-order conditions are

$$p^{TPS} = c_i(q_i^{TPS}) + \theta_i, \quad \pi_i + p^{TPS}\breve{\beta}_i = \kappa_i(y_i^{TPS}).$$

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

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

By the clearance of the market of abatement targets, we have

$$\sum_{i=1}^{N} q_i^{TPS} = \sum_{i=1}^{N} \breve{q}_i^{TPS} = \sum_{i=1}^{N} (\bar{e}_i - \breve{\beta}_i y_i^{TPS}).$$

The equilibrium conditions are then as described

(3) Welfare Implications, TPS vs. Regular Market

Comparing Lemmas 5 and 6, we see that the TPS scheme differs from the regular market scheme in the additional term $p^{TPS}\breve{\beta}_i$ in the first-order condition for the output market. This has at least two implications. First, the welfare outcome in the output market

under the TPS scheme would differ from that under the regular market scheme. Second, under the TPS scheme, since p^{TPS} is uncertain ex ante, the policy designer generally cannot pin down y_i^{TPS} by the first-order condition for the output market ex ante. Thus, she cannot pin down the total abatement in equilibrium, $Q^{TPS} \equiv \sum_{i=1}^{N} q_i^{TPS}$, ex ante, either.

As we have analyzed the welfare implications of the regular market, planning, and hybrid schemes in terms of the total abatement cost and local externalities, to make the welfare implications of the TPS scheme comparable, we still consider only the total abatement cost and local externalities, ignoring the welfare implications in the output market and the potential global externality of the abatement. The expected welfare difference between the TPS and regular market schemes is thus defined by

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

Proposition 4. *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 difference between the TPS and regular market schemes can be approximated and bounded by* $\Delta W^{TPS-Market} \lesssim \frac{S}{2} \cdot \left(\left(\bar{x} - \frac{Q}{S} - \bar{c}(0)\right)^2 + \bar{V}_\theta\right) \equiv \overline{\Delta W}^{TPS-Market}$, *where* $w_i \equiv \frac{\frac{1}{c_i'}}{\sum_{i=1}^{N}\frac{1}{c_i'}} > 0, \quad S \equiv \sum_{i=1}^{N}\frac{1}{c_i'} > 0, \quad \bar{x} \equiv \sum_{i=1}^{N} w_i\, x_i, \quad \bar{c}(0) \equiv \sum_{i=1}^{N} w_i\, c_i(0), \quad \bar{V}_\theta \equiv \sum_{i=1}^{N} w_i^2\, \sigma_i^2.$

Proof. By approximating $c_i''(q_i) \approx 0$ and $x_i''(q_i) \approx 0$, we can approximate

$$\begin{aligned}
&\int_0^{q_i^{TPS}} (x_i(q) - \theta_i - c_i(q))\, dq \\
&\approx \int_0^{q_i^{m}} (x_i(q) - \theta_i - c_i(q))\, dq + (x_i(q_i^m) - \theta_i - c_i(q_i^m))\left(q_i^{TPS} - q_i^m\right) \\
&\quad + \frac{x_i'(q_i^m) - c_i'(q_i^m)}{2} \cdot \left(q_i^{TPS} - q_i^m\right)^2.
\end{aligned}$$

Therefore, we can approximate

$$\int_0^{q_i^{TPS}} (x_i(q) - \theta_i - c_i(q))\, dq - \int_0^{q_i^m} (x_i(q) - \theta_i - c_i(q))\, dq$$
$$\approx (x_i(q_i^m) - \theta_i - c_i(q_i^m))\left(q_i^{TPS} - q_i^m\right) + \frac{x_i'(q_i^m) - c_i'(q_i^m)}{2} \cdot \left(q_i^{TPS} - q_i^m\right)^2.$$

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

$$\int_0^{q_i^{TPS}} (x_i(q) - \theta_i - c_i(q))\, dq - \int_0^{q_i^m} (x_i(q) - \theta_i - c_i(q))\, dq$$
$$\approx (x_i(q_i^m) - p^m)\left(q_i^{TPS} - q_i^m\right) + \frac{x_i'(q_i^m) - c_i'(q_i^m)}{2} \cdot \left(q_i^{TPS} - q_i^m\right)^2.$$

Therefore, we have

$$\sum_{i=1}^{N}\left(\int_0^{q_i^{TPS}} (x_i(q) - \theta_i - c_i(q))\, dq - \int_0^{q_i^m} (x_i(q) - \theta_i - c_i(q))\, dq\right)$$
$$\approx \sum_{i=1}^{N}\left((x_i(q_i^m) - p^m)\left(q_i^{TPS} - q_i^m\right) + \frac{x_i'(q_i^m) - c_i'(q_i^m)}{2} \cdot \left(q_i^{TPS} - q_i^m\right)^2\right).$$

Writing $c_i'(q_i) \approx c_i'$, further approximating $x_i'(q_i) \approx 0$, and writing $x_i(q_i) \approx x_i$, we then have

$$\sum_{i=1}^{N}\left(\int_0^{q_i^{TPS}} (x_i(q) - \theta_i - c_i(q))\, dq - \int_0^{q_i^m} (x_i(q) - \theta_i - c_i(q))\, dq\right)$$
$$\approx \sum_{i=1}^{N}\left((x_i - p^m) \cdot \left(q_i^{TPS} - q_i^m\right) - \frac{1}{2} \cdot c_i' \cdot \left(q_i^{TPS} - q_i^m\right)^2\right).$$

Now focus on $q_i^{TPS} - q_i^m$. By $c_i'(q_i) \approx c_i'$, $x_i(q_i) \approx x_i$, $c_i(q_i^m) + \theta_i = p^m$, $c_i(q_i^{TPS}) + \theta_i = p^{TPS}$, $\sum_{i=1}^N q_i^m = Q$, and $\sum_{i=1}^N q_i^{TPS} = Q^{TPS}$, we can approximate

$$q_i^m \approx \frac{\frac{Q - \sum_{i=1}^N \frac{-c_i(0) - \theta_i}{c_i'}}{\sum_{i=1}^N \frac{1}{c_i'}} - c_i(0) - \theta_i}{c_i'}, \quad q_i^{TPS}$$
$$\approx \frac{\frac{Q^{TPS} - \sum_{i=1}^N \frac{-c_i(0) - \theta_i}{c_i'}}{\sum_{i=1}^N \frac{1}{c_i'}} - c_i(0) - \theta_i}{c_i'},$$

and thus

$$q_i^{TPS} - q_i^m \approx \frac{\frac{Q^{TPS} - Q}{\sum_{i=1}^N \frac{1}{c_i'}}}{c_i'} = \frac{\frac{1}{c_i'}}{\sum_{i=1}^N \frac{1}{c_i'}} \cdot (Q^{TPS} - Q).$$

We thus have

$$\sum_{i=1}^N \left(\int_0^{q_i^{TPS}} (x_i(q) - \theta_i - c_i(q))\, dq - \int_0^{q_i^m} (x_i(q) - \theta_i - c_i(q))\, dq \right)$$
$$\approx \sum_{i=1}^N \left((x_i - p^m) \cdot \frac{\frac{1}{c_i'}}{\sum_{i=1}^N \frac{1}{c_i'}} \cdot (Q^{TPS} - Q) - \frac{1}{2} \cdot c_i' \cdot \left(\frac{\frac{1}{c_i'}}{\sum_{i=1}^N \frac{1}{c_i'}} \cdot (Q^{TPS} - Q) \right)^2 \right)$$
$$= \left(\sum_{i=1}^N w_i\, (x_i - p^m) \right) \cdot (Q^{TPS} - Q) - \frac{1}{2} \cdot \left(\sum_{i=1}^N \frac{1}{c_i'} \right) \cdot \left(\frac{Q^{TPS} - Q}{\sum_{i=1}^N \frac{1}{c_i'}} \right)^2$$
$$= (\bar{x} - p^m) \cdot (Q^{TPS} - Q) - \frac{1}{2S} \cdot (Q^{TPS} - Q)^2,$$

where

$$w_i \equiv \frac{\frac{1}{c_i'}}{\sum_{i=1}^N \frac{1}{c_i'}} > 0, \quad S \equiv \sum_{i=1}^N \frac{1}{c_i'} > 0, \quad \bar{x} \equiv \sum_{i=1}^N w_i\, x_i.$$

Note that $(\bar{x} - p^m) \cdot (Q^{TPS} - Q) - \frac{1}{2S} \cdot (Q^{TPS} - Q)^2$ is a quadratic function of $Q^{TPS} - Q$ with a negative quadratic term. Therefore, we have

$$(\bar{x} - p^m) \cdot (Q^{TPS} - Q) - \frac{1}{2S} \cdot (Q^{TPS} - Q)^2 \leq \frac{S}{2} \cdot (\bar{x} - p^m)^2.$$

Therefore, we have

$$\begin{aligned} \Delta W^{TPS-Market} &\approx \boldsymbol{E}\left[(\bar{x} - p^m) \cdot (Q^{TPS} - Q) - \frac{1}{2S} \cdot (Q^{TPS} - Q)^2\right] \\ &\leq \boldsymbol{E}\left[\frac{S}{2} \cdot (\bar{x} - p^m)^2\right] = \frac{S}{2} \cdot \boldsymbol{E}[(\bar{x} - p^m)^2]. \end{aligned}$$

Further note that, by $p^m = c_i(q_i^m) + \theta_i \approx c_i(0) + c_i' \cdot q_i^m + \theta_i$ and $Q = \sum_{i=1}^N q_i^m$, we have

$$p^m \approx \frac{Q + \sum_{i=1}^N \frac{c_i(0) + \theta_i}{c_i'}}{\sum_{i=1}^N \frac{1}{c_i'}}.$$

Therefore, by $\boldsymbol{E}[\theta_i] = 0$, $\boldsymbol{E}[\theta_i^2] = \sigma_i^2$, and mutual independence among all θ_is, we have

$$\begin{aligned} \boldsymbol{E}[(\bar{x} - p^m)^2] &\approx \boldsymbol{E}\left[\left(\bar{x} - \frac{Q + \sum_{i=1}^N \frac{c_i(0) + \theta_i}{c_i'}}{\sum_{i=1}^N \frac{1}{c_i'}}\right)^2\right] \\ &= \boldsymbol{E}\left[\left(\bar{x} - \frac{Q}{S} - \sum_{i=1}^N w_i\, c_i(0) - \sum_{i=1}^N w_i\, \theta_i\right)^2\right] \\ &= \boldsymbol{E}\left[\left(\bar{x} - \frac{Q}{S} - \sum_{i=1}^N w_i\, c_i(0)\right)^2\right] + \boldsymbol{E}\left[\left(\sum_{i=1}^N w_i\, \theta_i\right)^2\right] \\ &= \left(\bar{x} - \frac{Q}{S} - \sum_{i=1}^N w_i\, c_i(0)\right)^2 + \sum_{i=1}^N w_i^2\, \boldsymbol{E}[\theta_i^2] \\ &= \left(\bar{x} - \frac{Q}{S} - \bar{c}(0)\right)^2 + \sum_{i=1}^N w_i^2\, \sigma_i^2 = \left(\bar{x} - \frac{Q}{S} - \bar{c}(0)\right)^2 + \bar{V}_\theta, \end{aligned}$$

where

$$\bar{c}(0) \equiv \sum_{i=1}^{N} w_i \, c_i(0), \quad \bar{V}_\theta \equiv \sum_{i=1}^{N} w_i^2 \, \sigma_i^2.$$

We thus have

$$\Delta W^{TPS-Market} \lesssim \frac{S}{2} \cdot \left(\left(\bar{x} - \frac{Q}{S} - \bar{c}(0) \right)^2 + \bar{V}_\theta \right) \equiv \overline{\Delta W}^{TPS-Market}.$$

The proposition is thus proved. ∎

Proposition 4 suggests that, ex ante, when considering only the abatement costs and local externalities, even if the TPS scheme may improve upon the regular market scheme, the improvement would be no more than approximately $\overline{\Delta W}^{TPS-Market}$.

Recall that

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

where

$$D_x \equiv \sum_{i=1}^{N} (w_i \cdot (x_i - \bar{x})^2).$$

Therefore, the expected welfare loss under the TPS scheme, relative to the ex-post socially optimal allocation, is bounded from below by approximately

$$\begin{aligned} \Delta W^{TPS} &= \Delta W^{Market} - \Delta W^{TPS-Market} \gtrsim \Delta W^{Market} - \overline{\Delta W}^{TPS-Market} \\ &= \frac{S}{2} \cdot \left(D_x - \left(\bar{x} - \frac{Q}{S} - \bar{c}(0) \right)^2 - \bar{V}_\theta \right) \equiv \underline{\Delta W}^{TPS}. \end{aligned}$$

We can thus compare $\underline{\Delta W}^{TPS}$ with ΔW^{Market} and ΔW^{Hybrid} to see the welfare-improving potential of the TPS scheme. Compared to what we have already, this calculation would need in addition Q and $\bar{c}(0)$. We can also compare directly $\overline{\Delta W}^{TPS-Market}$ with the welfare improvement from any hybrid scheme relative to the

market approach. Figure S8 plots the result based on our empirical analysis in the main text, where $\underline{\Delta W}^{Best\ Hybrid-Market}$ is calculated as the difference between the expected welfare loss under the best hybrid scheme in our illustration in the main text, and the expected welfare loss under the market approach.

Appendix I. 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) (Färe et al. 1993a, 2005; Chung et al. 1997).

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:

$$P(x) = \{(y, b): x \text{ can produce } (y, b)\}.^{1}$$

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 $0 \leq \theta \leq 1$.

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

Given this production possibility set, we can use the Shephard output distance functions to represent technology (Shephard 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.[2] After choosing the directional vector and function form of 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 non-parametrically 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

[2] 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.

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

Figure S1 summarizes our estimated Marginal Abatement Cost (MAC) for each province in 2012. The monetary values here are all adjusted to the 2015 level. The DDF method is widely used by the China's scholars to estimate the MAC at both regional and industrial scales (Ma et al. 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 J. 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:

$$Deaths_i = \frac{\beta_{AQI-Carbon} * M_{i,2021} * AQI_{i,2021}}{10} * MR * 3.8\% * Pop_i * 52,$$

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, $\frac{1\text{ ton}}{CO_2\text{ Emissions in Province } i \text{ in } 2017}$. $AQI_{i,2021}$ is the AQI levels in province *i* in 2-21. Hence, $\beta_{AQI-Carbon} * M_{i,2021} * AQI_{i,2021}$ calculates 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 et al. 2020).[3] Pop_i is the population size in province i in 2021. 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.[4] 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 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

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

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

Barwick et al. (2026) research finds that 10-μg/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:

$$Cost_Morbidity_i = \frac{\beta_{PM2.5-Carbon} * M_{i,2021} * PM2.5_{i,2021}}{10} * Pop_i/3 * 73.45,$$

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 2021. 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-μg/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 of 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:

$$Cost_{GDP_i} = \beta_{PM2.5-Carbon} * 0.038\% * GDP_{i,2021},$$

where $GDP_{i,2017}$ is the GDP in each province in 2021. Column 6 of Table S3 summarizes the corresponding results, where we find that one million tons of emissions of CO_2 can reduce the GDP by 19.15 million USD on average.

Appendix K. Bootstrapping Distributions of Estimates

To obtain the distributions of the estimates of ΔW^{Market} and ΔW^{Plan}, we need to have the distributions of the estimates of four parameters for each province, i.e., the incomplete information σ_i, the MACC slopes a_i, the carbon-pollution correlation β_i, and the marginal external cost of carbon x_i.

In our paper, we estimate β_i and derive its distribution using the estimates and standard errors as presented in Table 2. We obtained x_i from literature, which also provides corresponding estimates and standard errors so that we can establish its population distribution.

The distributions of σ_i and a_i are obtained simultaneously when deriving the marginal abatement cost curve for each province. In our baseline analysis, there is no distribution explicitly assigned to the estimate of σ_i since it is calculated as the standard estimate of errors:

$$\sigma_i = \sqrt{\sum \left(CO_2Price_{i,t} - \widehat{CO_2Price_{i,t}}_{i,t}\right)^2 /(n-2)}.$$

To obtain a distribution of the estimate of σ_i, we return to its corresponding estimating equation and employ bootstrapping approaches by constructing a population distribution of the independent variable. Recall that we obtain σ_i and a_i by running the following regression for each province using the data between 2012 and 2021:

$$CO_2Price_{i,t} = a_i CO_2Reduction_{i,t} + b_i + \varepsilon_{i,t}.$$

The above regression represents province i's marginal abatement cost curve function. We calculate $CO_2Price_{i,t}$, which represents or province i's marginal abatement cost of carbon in year t, using the DDF method. $CO_2Reduction_{i,t}$ is obtained via two steps: first, we run the following regression using the pre-2012 data:

$$CO_2Emission_{i,t\leq 2011} = b_1 GDP_{i,t\leq 2011} + b_2 year_{t\leq 2011} + \varepsilon_{i,t}.$$

Then we employ post-2012 GDP and year dummies as predictors to construct the counterfactual carbon emissions between 2012 and 2021. By comparing the actual carbon emissions with the predicted counterfactual emissions, we calculate the magnitude of carbon reduction in each province-year, denoted as $CO_2Reduction_{i,t}$. These two-stage regressions enable us to derive a distribution of $CO_2Reduction_{i,t}$ for each province-year, which can subsequently be used to estimate the distributions of a_i and σ_i. Overall, we obtain 8000 bootstrapped-sample estimates of ΔW^{Market} and ΔW^{Plan}.

Figure S6 plots the distributions of the 8,000 bootstrapped-sample estimates of the expected welfare losses. Table S4 reports the result from Kolmogorov–Smirnov tests of the equality of two distributions (Conover 1999). Results imply that ΔW^{Plan} statistically significantly contain smaller values than ΔW^{Market}, and the largest difference between the distribution functions is 0.669. In Figure S7, we further plot the distribution of the bootstrapped-sample estimates of $\Delta W^{Plan} - \Delta W^{Market}$ (Panel A) and its corresponding empirical cumulative distribution function (Panel B). Again, the distribution of the estimate of $\Delta W^{Plan} - \Delta W^{Market}$ is centered at a negative value and most of the distribution falls onto the negative range.

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Appendix Tables and Figures

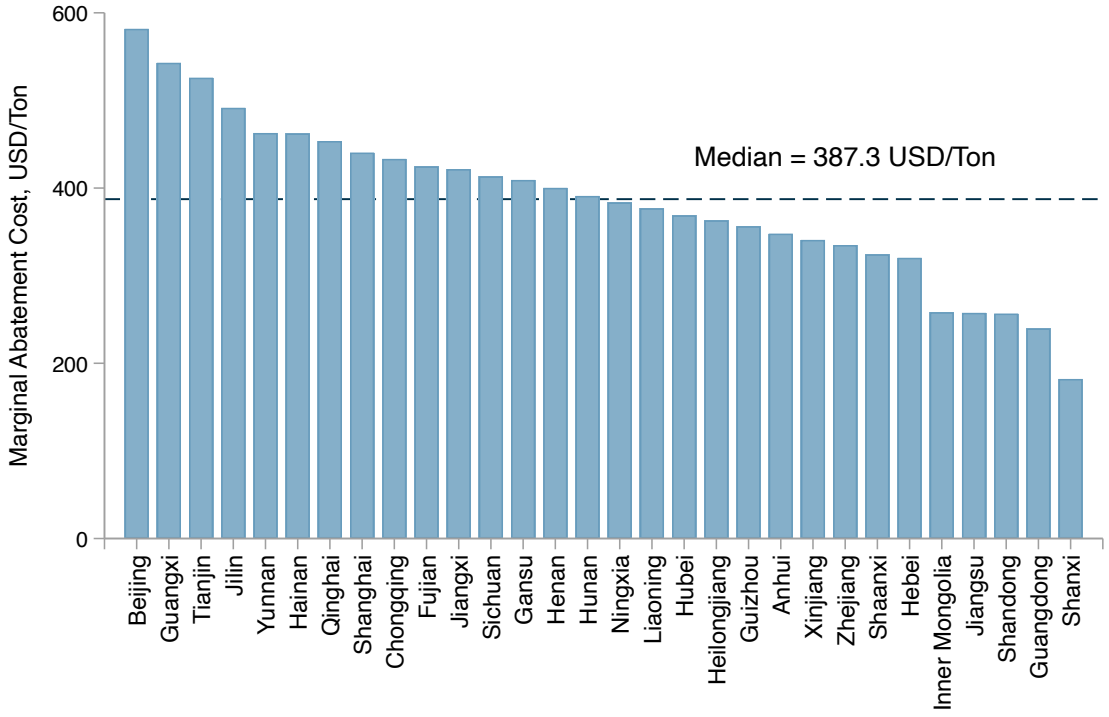


Figure S1. Estimated Average Provincial Marginal Abatement Cost (MAC) of Carbon Emissions in 2012

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

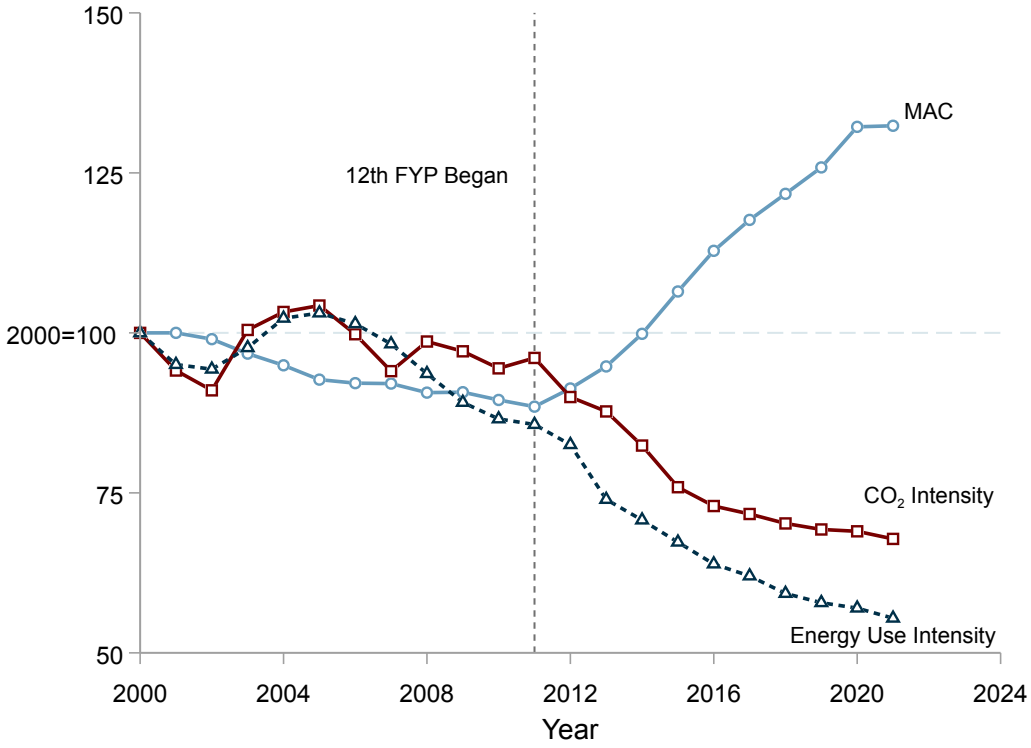


Figure S2. Trends of Intensity Measures and Estimated MACs of CO_2 Emissions (2000–2021)

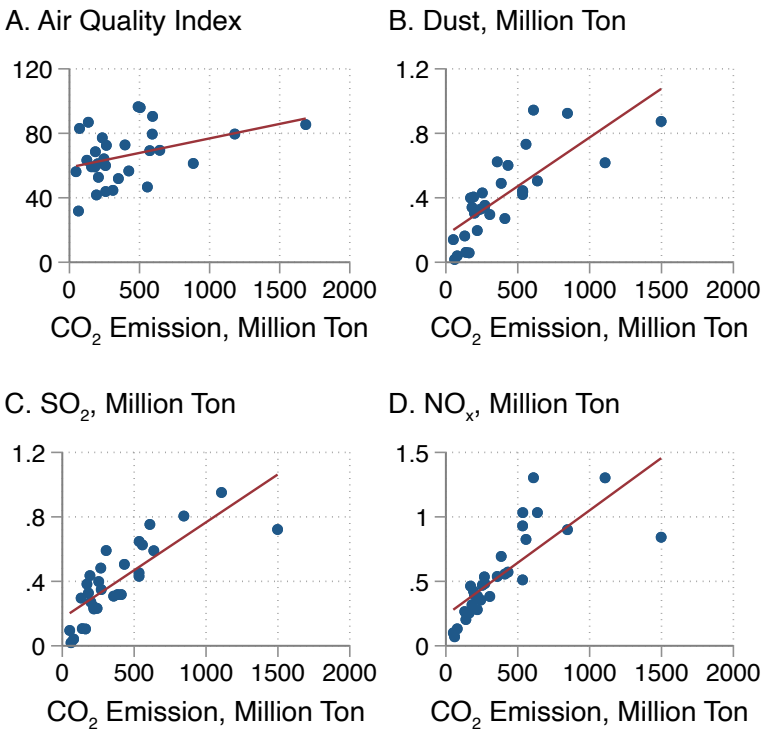


Figure S3. Carbon Emissions and Air Pollution

Notes: Each dot represents a province. Panel A plots the relationship between carbon emissions and the ambient air quality measures, i.e., Air Quality Index. 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. We take the averages of these variables from 2015 to 2021 to plot the figure. Panels B to D plots the relationship between carbon emissions and emissions of different air pollutants using provincial data. We take the averages of these variables from 2011 to 2021 to plot the figure.

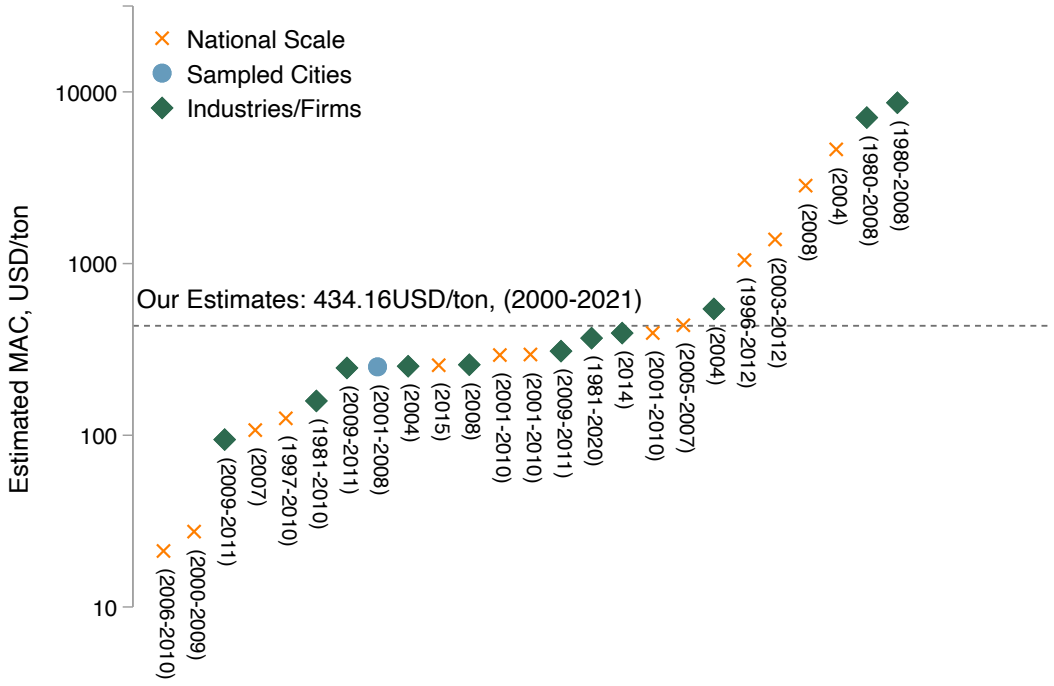


Figure S4. Estimates of Marginal Abatement Cost in the Literature

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 2021. 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.

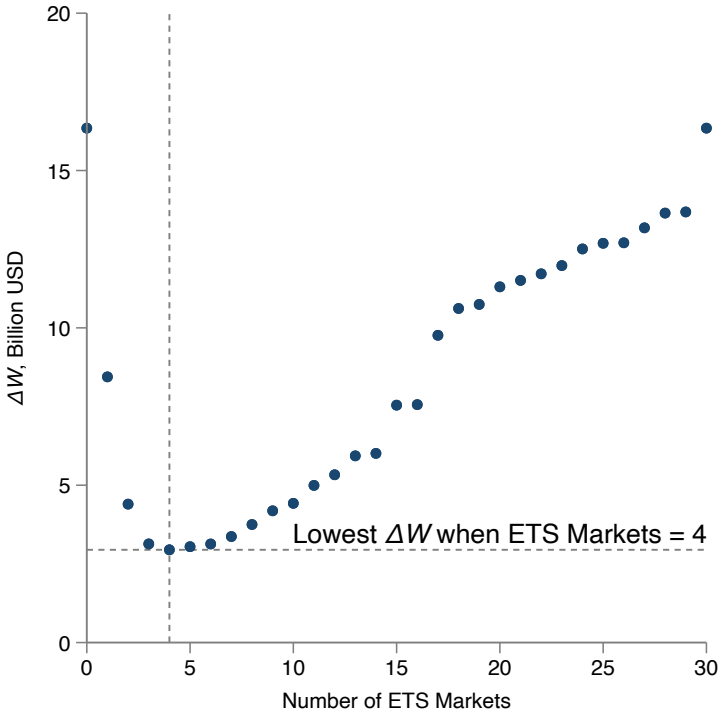


Figure S5. Lowest Expected Welfare Losses under Hybrid Schemes

Note: In each hybrid scheme, we first rank the 30 Chinese provinces 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 separate markets of equal number of provinces by their marginal local externalities of abatement. We plot the lowest expected welfare loss case along the number of separate markets in each hybrid scheme.

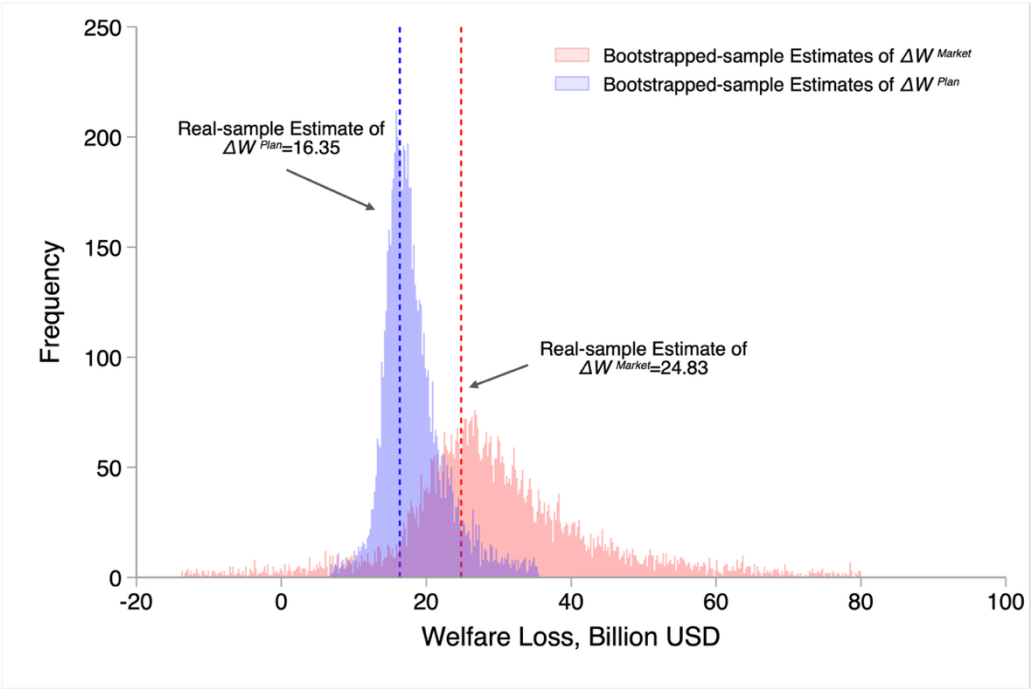
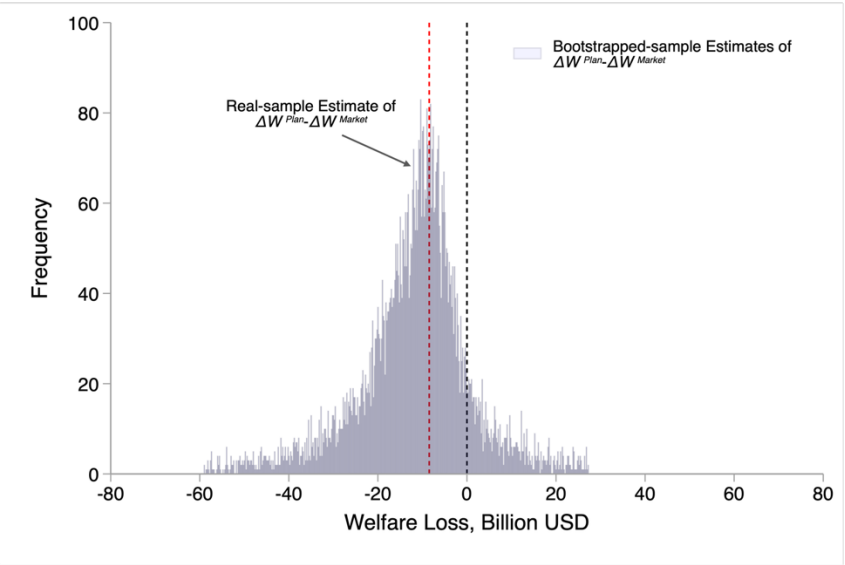
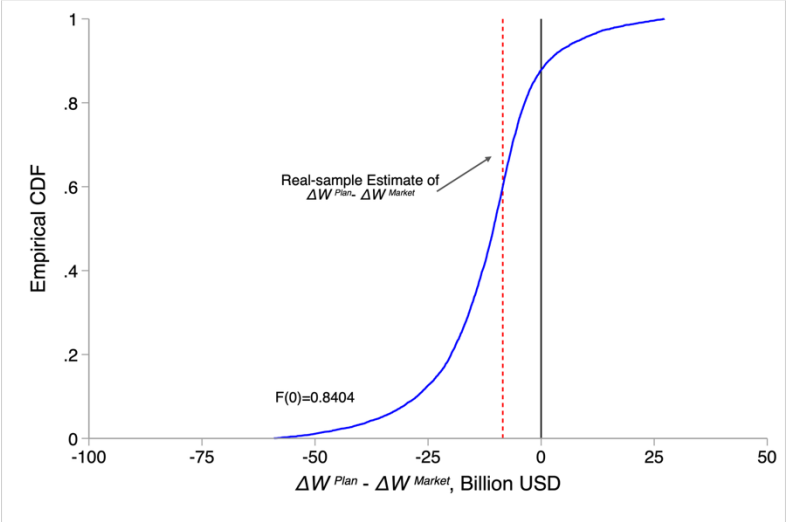


Figure S6. Compare Expected Welfare Losses between Market and Planning.

Notes: The vertical red depicts the real-sample estimate of ΔW^{Market}, which is the expected welfare loss under the market caused by failing to address heterogeneous local externalities. The blue line shows the real-sample estimate of ΔW^{Plan}, which is the expected welfare loss under planning caused by failing to address incomplete information. The light red and light blue bars indicate distributions of 8000 bootstrapped-sample estimates of ΔW^{Market} and ΔW^{Plan}, respectively. We drop the top 5% and bottom 5% estimates of ΔW^{Market} and ΔW^{Plan} for exposition.



Panel A. Distribution of Bootstrapped-sample Estimates of $\Delta W^{Plan} - \Delta W^{Market}$



Panel B. Empirical Cumulative Distribution Function (CDF) of $\Delta W^{Plan} - \Delta W^{Market}$

Figure S7. Distribution of Bootstrapped-sample Estimates of Expected Welfare Loss Differences between Market and Planning.

Notes: In Panel A, the light grey bars represent the distribution of bootstrapped-sample estimates of expected welfare loss differences between ΔW^{Plan} (blue area in Figure S6) and ΔW^{Market} (red area in Figure S6). The vertical red depicts the real-sample estimate of the difference between ΔW^{Plan} and ΔW^{Market}. Panel B plots the empirical

cumulative distribution function of the bootstrapped-sample estimates of $\Delta W^{Plan} - \Delta W^{Market}$ shown in Panel A.

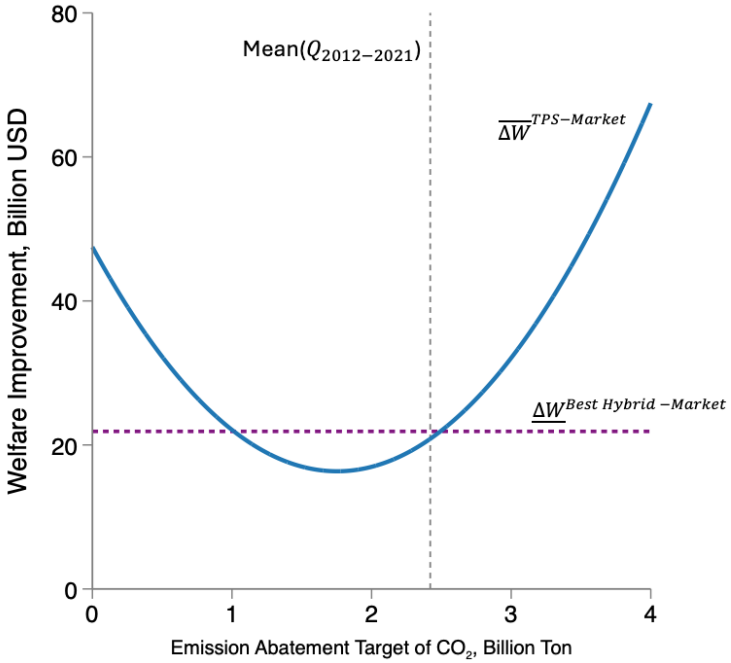


Figure S8. Bounds of Potential Expected Welfare Improvement under TPS and Hybrid Schemes Relative to the Market-alone Scheme

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 Associations between CO_2 Emissions and Air Pollutant and Emissions

	AQI	$PM_{2.5}$	PM_{10}	SO_2	NO_2	CO	O_3	Industrial Dust
	(log)	(log)	(log)	(log)	(log)	(log)	(log)	(log)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CO_2 Emissions	0.28***	0.28***	0.39***	0.09	0.27*	0.07	0.08	0.49**
(Million Ton, log)	(0.06)	(0.09)	(0.07)	(0.23)	(0.11)	(0.12)	(0.05)	(0.19)
Unit	points	$\mu g/m^3$	$\mu g/m^3$	$\mu g/m^3$	$\mu g/m^3$	mg/m^3	$\mu g/m^3$	Million Ton
R-Squared	0.98	0.97	0.98	0.95	0.97	0.93	0.89	0.98
Weather Controls	Y	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	210	210	210	210	210	210	210	210
Number of Provinces	30	30	30	30	30	30	30	30

Notes: Each column reports a separate regression on the correlation between CO_2 emissions and air pollution and emissions using the provincial data from 2015 to 2021. In Columns (1) to (7), 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. In Column (8), the dependent variable is the provincial level logarithm of industrial dust emissions. 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 (1)	Pre-Mature Deaths (Number) (2)	Monetary Values of (2) (Annually) (3)	Morbidity Expenditures (Annually) (4)	Defensive Expenditures (Annually) (5)	Economic Cost (Annually) (6)	Reduced Life Expectancy (Thousand Years) (7)	Monetary Values of (7) (Million USD) (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 I. 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) are measured by million USD (deflated to the 2015 level).

Table S4. Kolmogorov–Smirnov Tests of the Equality of Two Bootstrapped-sample Estimates

(1) Smaller Group	(2) D	(3) *p*-value
1 ($\Delta W^{Plan} < \Delta W^{Market}$)	-0.6687	0.000
2 ($\Delta W^{Plan} > \Delta W^{Market}$)	0.4276	0.000
Combined K-S	0.5485	0.000

Notes: The second and the third rows report the Kolmogorov-Smirnov tests results of hypothesis that ΔW^{Market} contains larger and smaller numbers than ΔW^{Plan}, respectively. Column (2) in the first and the third rows indicate the largest difference between two distribution functions, with Column (3) showing the approximate asymptotic *p*-value. The last row reports the combined test results.