Environmental Regulation and Within-Firm Adjustment: Evidence from Chinese Steel*

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Abstract

Firms can comply with environmental regulation by changing production processes or by abating pollution after it is generated; yet the production margin remains largely a black box. This paper opens it using stage-level production, environmental, and financial data for Chinese steel firms. We exploit within-province variation in regulatory pressure under the 2016–2020 Good-Air Days targets in a difference-in-differences design. Firms facing greater pressure rely less on the pollution-intensive upstream stages and invest more in abatement. A one-standard-deviation increase in target intensity reduces pig iron input per ton of crude steel by 2.4% of its mean, implying a 2.2-percentage-point rise in scrap's share of metal inputs. Environmental investment rises by 49% of its mean, concentrated in air-pollution control. Pre-tax profit per ton does not fall. The production adjustment implies only a small reduction in reported SO_2 emissions. Evaluations based solely on emissions or financial outcomes would overlook the production margin.

Keywords: Environmental Regulation; Production-process Adjustment; Material-input Substitution; Abatement Investment; Chinese Steel

JEL codes: Q52, Q53, L61, D22

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1 Introduction

Emissions of common air pollutants from US manufacturing fell by 60% between 1990 and 2008 even as output grew, mainly because environmental regulation reduced emissions per unit of output within the same products (Shapiro and Walker, 2018). Yet how firms achieved these reductions remains largely a black box. Firms can change production so that less pollution is generated in the first place (the production margin) or install end-of-pipe equipment that removes pollutants after they are generated (the abatement margin).[1] Emissions data alone cannot distinguish the two margins: they generally record pollution net of abatement, so a given decline could reflect either margin. The distinction matters because the margins differ in what they cost firms and in whether the gains persist once monitoring eases (Zhang et al., 2025). This paper asks whether firms facing tighter regulation adjust production, increase end-of-pipe abatement, or both, and how their emissions and profits move alongside these choices.

Separating the two margins is challenging: it requires data on production choices within firms, which most evaluations of environmental regulation lack. These evaluations focus on outcomes such as emissions, productivity, and profits, and seldom observe the production decisions behind them (Dechezleprêtre and Sato, 2017). Studies that distinguish the two margins typically infer the production margin indirectly, from emissions data or abatement expenditures (Dutt and King, 2014; Liu et al., 2022; Qi et al., 2023; Fan et al., 2025a; Zhang et al., 2025), rather than measuring it directly.

China's steel industry provides a useful setting for studying both production adjustments and end-of-pipe abatement. China has been the world's largest crude-steel producer since 1996 and accounted for 53.4% of global output in 2024.[2] Steel is also China's largest industrial source of particulate matter, SO_2, and NO_x.[3] The dominant blast-furnace–basic-oxygen-furnace (BF–BOF)

[1] Prior work studies compliance margins largely one at a time, including abatement investment (Barbera and McConnell, 1990; Colmer et al., 2025; Fan et al., 2025a); entry, investment, and market-structure responses to higher entry costs (Ryan, 2012); intra-firm pollution substitution (Rijal and Khanna, 2020); temporary cuts in operating hours and output (Liu et al., 2027); technology adoption and test gaming under vehicle emission standards (Reynaert, 2021); and technology or technique change (Levinson, 2015; Shapiro and Walker, 2018; Gutiérrez and Teshima, 2018; Najjar and Cherniwchan, 2021).

[2] China first became the world's largest crude-steel producer in 1996; United Nations Economic Commission for Europe, "China ranks no. 1 in world production of steel in 1996," January 10, 1997, https://unece.org/fileadmin/DAM/press/pr1997/97ind1.htm. In 2024, China produced 1,005.1 million tons of crude steel out of 1,882.6 million tons worldwide. World Steel Association, "December 2024 crude steel production and 2024 global crude steel production totals," January 24, 2025, https://worldsteel.org/media/press-releases/2025/december-2024-crude-steel-production-and-2024-global-totals/.

[3] An official Ministry of Ecology and Environment analysis reports 2017 emission shares and finds that steel's emissions of the three pollutants exceeded those of the power sector, making steel the largest industrial source; https://www.mee.gov.cn/xxgk2018/xxgk/xxgk15/201905/W020190505657985649751.pdf. For evidence on Chinese iron- and steelmaking emissions, see Bo et al. (2021). For evidence on the costs of air pollution from steel plants in China, see Chen (2025).

route vertically integrates several production stages: firms agglomerate iron ore into sinter, smelt it into pig iron, and refine pig iron into crude steel. Sintering and ironmaking account for most of the industry's emissions. Firms can reduce their reliance on these upstream stages by substituting scrap steel for pig iron in basic oxygen converters, subject to heat-balance, mixing, and scrap-quality constraints (He et al., 2020; Voraberger et al., 2022; Schäfer et al., 2025). This raises the converter scrap share, the fraction of the converter's metallic input that is scrap (known in the industry as the scrap ratio, *feigangbi* in Chinese), and reduces sintering and ironmaking per ton of crude steel. Observing production at both upstream and downstream stages therefore allows us to trace input substitution within firms, while environmental investment captures the end-of-pipe abatement margin.

We use annual production-stage data from the China Iron and Steel Association (CISA), which report output at each stage of steel production, environmental investment, SO_2 emissions, financial outcomes, and purchased scrap for a subset of firms. We link these records to city-level Good-Air Days targets under the 13th Five-Year Plan for Ecological and Environmental Protection (2016–2020). A Good-Air Day is defined as a day with an Air Quality Index of 100 or below. For a given target, cities with poorer baseline air quality needed larger improvements and thus faced greater regulatory pressure. Local officials were evaluated on progress toward these targets and imposed production restrictions during heavy-pollution alerts, seasonal production cuts, and stricter emission standards on steel plants. Because restrictions could target individual production stages, plants could maintain crude-steel output despite cuts to sintering or ironmaking by increasing the share of scrap charged into converters.

We use a difference-in-differences design to compare changes in firm outcomes before and after the Good-Air Days targets took effect in 2016, across cities within the same province that faced different levels of regulatory pressure. We measure this pressure using target intensity, defined as the ratio of a city's end-of-plan Good-Air Days target to its average number of Good-Air Days in 2014–2015. A higher ratio indicates a larger required improvement relative to baseline air quality.[4] An event-study analysis assesses whether firms facing different target intensities followed similar outcome trends before 2016. The targets were part of a broader clean-air regulatory regime that also placed greater pressure on more polluted cities. We therefore interpret our estimates as responses to differential local regulatory pressure, proxied by target intensity, rather than the isolated causal effect of the targets.

We document two responses. First, firms change how they produce steel. In cities facing greater regulatory pressure, the pig-iron-to-crude-steel ratio falls. A one-standard-deviation increase in

[4]Section 2 describes the Good-Air Days indicator, and Section 3 presents the distribution of target intensity in our sample. The 13th Five-Year Plan for Ecological and Environmental Protection designated the share of Good-Air Days in prefecture-level cities as a binding environmental indicator. Source: State Council, https://www.mee.gov.cn/zcwj/gwywj/201811/t20181129_676583.shtml.

target intensity reduces this ratio by 2.4% of its mean. Because pig iron and scrap are the two metallic inputs in converter steelmaking, this reduction suggests that firms substitute scrap for pig iron. The implied converter scrap share rises by approximately 2.2 percentage points. The sintering-to-crude-steel ratio also falls, consistent with less upstream processing per ton of crude steel. Crude-steel output remains largely unchanged, indicating that firms adjust their input mix rather than reduce production.

Second, firms increase spending on end-of-pipe abatement. A one-standard-deviation increase in target intensity is associated with approximately 117 million CNY (2015 prices) in additional environmental investment, equivalent to 49% of the sample mean, with most of the increase directed toward air-pollution control. The investment response is concentrated in northern cities that also faced intensified winter air-pollution controls. The two adjustment margins differ across firms: input substitution is driven primarily by private and smaller firms, whereas environmental investment increases across all ownership and size groups.

Purchased-scrap data provide further evidence that firms substitute scrap for pig iron. Among firms reporting scrap purchases, a one-standard-deviation increase in target intensity within that subsample is associated with an additional 20.4 kg of purchased scrap per ton of crude steel, equivalent to 29% of the subsample mean. Because the survey covers fewer firms and excludes Hebei, China's largest steel-producing province, we use this evidence to corroborate the direction of substitution.

Our comparison is between cities within the same province and year, so a confounding factor would need to vary across cities within a province, correlate with baseline air quality, and affect outcomes from 2016 onward. Differential trends associated with baseline air quality are the main concern, but several findings weigh against this explanation. The production ratios show no differential pre-policy trends and begin to decline in 2017, while crude-steel output remains unchanged and purchased scrap increases. The adjustment is concentrated in sintering and ironmaking, the stages targeted by production restrictions. The pig-iron response is also largest in the highest tercile of target intensity when the 14 locations that already met their targets, and thus faced no required improvement, serve as the comparison group.

Reported SO_2 emissions reflect little of this input substitution. A back-of-the-envelope calculation based on our estimates implies only a small reduction in reported SO_2. Firms may also respond to lower SO_2 generation by operating desulfurization equipment less intensively, taking part of the gain as lower treatment costs rather than lower emissions. Our design cannot isolate this small reduction, because the SO_2 gap between firms in higher- and lower-intensity cities opened before the targets took effect and did not widen significantly afterwards.

Firms facing higher target intensity do not become less profitable. In the matched financial sample, a one-standard-deviation increase in target intensity is associated with roughly 73 CNY

(2015 prices) higher pre-tax profit per ton, about 1.3% of operating revenue per ton. Because the gain coincided with a steel-market recovery that may have affected cities unevenly, we cannot attribute it to regulatory pressure alone.

This paper makes two contributions. First, it contributes to the literature on firm adjustment to environmental regulation. Existing studies document responses along various margins, including emissions, investment, output, and productivity.[5] However, the underlying production adjustments are often inferred indirectly through decompositions, residual measures, or structural models (Levinson, 2015; Shapiro and Walker, 2018; Najjar and Cherniwchan, 2021; Chen et al., 2026; Lu and Pless, 2026). Direct evidence of regulation-induced input substitution focuses primarily on fuels and energy, including fuel switching in electricity generation (Carlson et al., 2000), interfuel substitution in manufacturing (Murray-Leclair, 2026), and changes in energy sources and product mix among Indian manufacturers (De Simone et al., 2025), and much less is known about substitution among material inputs. We provide direct evidence of material-input substitution using stage-level production data and scrap purchases from Chinese steel firms. This within-firm, within-route adjustment differs from reallocation across steelmaking technologies (Collard-Wexler and De Loecker, 2015), substitution across pollution media (Greenstone, 2003; Gibson, 2019), and pollution shifting across affiliated facilities (Rijal and Khanna, 2020; Jia et al., 2025).

Second, this paper contributes to the literature on how compliance strategies shape the costs of environmental regulation. A large literature finds mixed effects on innovation, productivity, and profitability.[6] These effects also depend on policy design and the adjustment horizon (Albrizio et al., 2017). Process improvements and resource efficiency are associated with private gains, whereas end-of-pipe treatment generally is not (King and Lenox, 2002; Rexhäuser and Rammer, 2014). In Chinese textile dyeing, stricter wastewater regulation reduces productivity more among firms relying on end-of-pipe treatment (Liu et al., 2022). In US manufacturing, pollution prevention improves technical and environmental efficiency, with material-input substitution emerging as the most consistent driver (Memon et al., 2026). These studies, however, identify compliance strategies through surveys or reported environmental data rather than observed production quantities. We directly measure changes in production inputs alongside environmental investment and profitability within the same firms.

This paper proceeds as follows. Section 2 covers steel production technology and the Good-Air Days policy; Section 3, the data and empirical strategy. Section 4 presents the main results

[5] These include emissions leakage, outbound FDI, and trade recomposition (Fowlie, 2009; Hanna, 2010; Levinson and Taylor, 2008); productivity costs of water regulation (He et al., 2020); export responses to the Eleventh Five-Year Plan (Shi and Xu, 2018); emissions-intensity and reallocation decompositions during the WTO-accession period (Rodrigue et al., 2022); exporting and abatement responses in firm-level emissions (Rodrigue et al., 2024); and coal-consumption reductions under Beijing's emissions trading scheme (Tian et al., 2026).

[6] See, for example, Porter and van der Linde (1995); Jaffe and Palmer (1997); Berman and Bui (2001); Calel and Dechezleprêtre (2016); Lanoie et al. (2011); Ambec et al. (2013); Cohen and Tubb (2018).

on production, purchased scrap, and environmental investment; Section 5, the robustness checks; and Section 6, which firms adjust on which margin. Section 7 discusses reported emissions and financial outcomes. Section 8 concludes.

2 Background

2.1 China's Steel Industry and Its Production Technology

China is the world's largest steel producer, accounting for more than half of global crude-steel output.[7] Unlike the United States, where electric arc furnaces account for about two-thirds of crude-steel production,[8] approximately 90% of China's crude steel comes from the *blast-furnace–basic-oxygen-furnace (BF–BOF) route* (He et al., 2020).[9] Iron ore fines and fluxes are first agglomerated into sinter. Sinter, lump ore, pellets, and coke are then charged into a blast furnace to produce pig iron, which is refined together with scrap steel in a basic oxygen furnace (BOF), also called a converter, to produce crude steel. Figure 1 illustrates this production route. Sintering and ironmaking are major sources of local air pollution. According to a comprehensive emissions inventory of Chinese steel producers, sintering accounts for 71% of SO_2, 73% of NO_x, and 54% of $PM_{2.5}$ emissions in the industry (Wu et al., 2024).

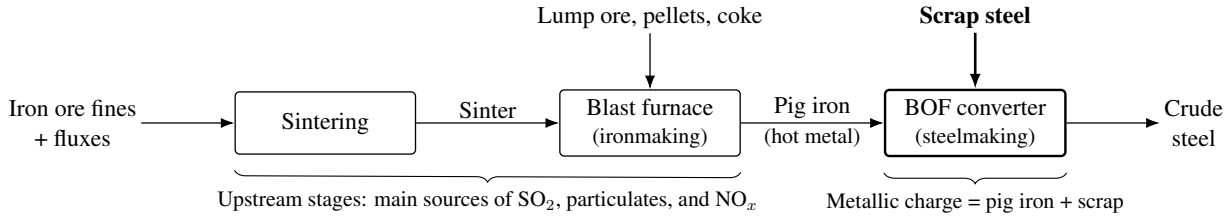


Figure 1: Simplified BF–BOF Steelmaking Route and Scrap Substitution Margin. *Notes*: This figure abstracts from plant-specific inputs, by-products, and downstream rolling. The substitution margin of interest is the converter input mix. A higher scrap share means less pig iron per ton of crude steel and can reduce upstream activity per ton of output, subject to heat-balance, mixing, and scrap-quality constraints.

The within-route adjustment we study is an increase in the *converter scrap share*, the fraction of the converter's metallic input that comes from scrap steel. Because scrap has already been pro-

[7] World Steel Association, *World Steel in Figures 2019*, reports China's crude-steel production at 870.9 million tons in 2017, compared with 1,729.8 million tons worldwide, and 928.3 million tons in 2018, compared with 1,808.4 million tons worldwide. See https://worldsteel.org/wp-content/uploads/2019-World-Steel-in-Figures.pdf.

[8] World Steel Association, *World Steel in Figures 2019*, reports the electric-furnace share of U.S. crude-steel production at 68% in 2018. See https://worldsteel.org/wp-content/uploads/2019-World-Steel-in-Figures.pdf.

[9] The electric route has remained marginal because industrial electricity is costly and scrap, though growing, remains relatively scarce. In 2020, China's scrap resources amounted to approximately 210 million tons, roughly one-fifth of its crude-steel output; scrap-based steelmaking requires approximately one ton of scrap per ton of steel (Deutsche Energie-Agentur (dena), 2023).

cessed into steel, substituting it for pig iron reduces the need for upstream sintering and ironmaking, along with the associated emissions. At modest shares, this substitution requires little change in production technology. Refining molten pig iron generates enough heat to melt some scrap, although differences in scrap quality complicate mixing and quality control. Under a conventional heat balance, the scrap share is typically around 15–20% (Voraberger et al., 2022). Raising the ratio beyond what the existing heat balance permits requires additional heat or equipment, such as scrap preheating, larger charging equipment, higher-silicon pig iron, or auxiliary fuels (Voraberger et al., 2022; Schäfer et al., 2025). The feasible scrap share is thus not fixed; firms can invest to raise it.

Neither this adjustment margin nor the underlying technology is unique to China. High-scrap converter processes were developed internationally in the 1970s and 1980s, after oxygen converters displaced scrap-intensive open-hearth furnaces, but never became the dominant means of recycling scrap. In 2016, converter scrap ratios in China were only about 7% (Shangguan et al., 2024), well below what conventional technology could accommodate without major modifications. Conditions then shifted in ways that made greater scrap use more attractive. Scrap supply was growing as steel produced in earlier decades reached the end of its useful life. The closure of induction-furnace mills in 2017, previously major users of scrap, further increased its availability and lowered its price relative to hot metal (Deutsche Energie-Agentur (dena), 2023; Lu, 2017). Meanwhile, sintering and ironmaking faced tighter environmental controls. With much of China's BF–BOF capacity already installed, firms could increase scrap use by modifying existing converters rather than building electric arc furnaces. This allowed them to produce more steel from a given amount of pig iron, or maintain output with less sintering and ironmaking, reducing pollution at the source.[10]

2.2 Good-Air Days Targets under the 2016–2020 Environmental-Protection Plan

China's clean-air policy shifted in the early 2010s from a primary focus on emissions reductions toward greater emphasis on ambient air-quality objectives. Earlier programs primarily targeted emissions reductions (Lu and Pless, 2026; Shi and Xu, 2018), whereas the 2013 Air Pollution Prevention and Control Action Plan emphasized measured local air quality. As a major source of particulate matter and SO_2, the steel industry became a focus of this shift (Bo et al., 2021; Wu et al., 2024).

The Outline of the 13th Five-Year Plan (2016–2020), approved by the National People's Congress on March 16, 2016, established the share of Good-Air Days in prefecture-level cities as a binding

[10] *Development of a New High-Scrap-Ratio, High-Efficiency, and Energy-Saving Converter Process*, an internal report (in Chinese) of the China Metallurgical Industry Planning and Research Institute, reviews earlier international processes and documents one such adjustment. A Tianjin BF–BOF producer increased its converter scrap share from 3.5% in 2016 to about 33% by late 2017 using the same three converters.

national indicator, with a target of increasing it from 76.7% in 2015 to more than 80% by 2020.[11] A Good-Air Day is defined as a day with an Air Quality Index (AQI) of 100 or below, where AQI is the maximum of pollutant-specific sub-indices. This target was introduced alongside other environmental and industrial policies that included the revised Environmental Protection Law, central environmental inspections, the "2+26" winter controls, the Blue Sky Defense campaign, steel supply-side reform, and the 2017 induction-furnace ban.[12] These policies differed in timing and geographic scope, as documented in Appendix Table A1.

The Good-Air Days target created accountability incentives for provincial governments. Performance on binding environmental indicators entered the evaluations of provincial leaders, with implications for promotion and discipline. Provincial governments further allocated air-quality targets to cities, with performance assessments conducted at successive administrative levels. At the prefectural level, officials adjusted their environmental efforts in response to air-quality targets (Cao et al., 2026). These incentives could, in turn, translate into regulatory pressure on firms through local environmental enforcement.[13]

Cities regulated steel plants through production restrictions, tighter emission standards, and inspections. Production restrictions were imposed during heavy-pollution alerts and, beginning in the winter of 2017–2018, through seasonal production cuts under the "2+26" controls. In 2019, the central government introduced ultra-low-emission requirements for the steel industry.[14]

Heavy-pollution alerts were issued based on forecasts of daily AQI above 200, making such restrictions more likely in highly polluted cities. Production restrictions could target specific production processes and equipment rather than entire plants, as reflected in the 2018 Blue Sky plan.[15]

[11] National People's Congress, *Outline of the 13th Five-Year Plan for National Economic and Social Development*, Box 2, item 23. Available at https://www.gov.cn/xinwen/2016-03/17/content_5054992.htm.

[12] Sources: central inspections, https://english.mee.gov.cn/News_service/news_release/201607/t20160721_361108.shtml; "2+26" controls, https://www.mee.gov.cn/xxgk/hjyw/201703/t20170330_409037.shtml; Blue Sky plan, https://www.forestry.gov.cn/main/4815/20180704/090001920658534.html; steel overcapacity, https://www.mofcom.gov.cn/zcfb/zgdwjjmywg/art/2016/art_6cd8647adfc64c13aae833151cc43fcb.html; induction-furnace ban, Chen et al. (2018).

[13] General Office of the CPC Central Committee and General Office of the State Council, Tingzi [2016] No. 45, Articles 2, 10, 13, and 19, https://www.mee.gov.cn/zcwj/zyygwj/201912/t20191225_751549.shtml. For the allocation of air-quality targets from provinces to cities, see Ministry of Ecology and Environment, https://www.mee.gov.cn/xxgk2018/xxgk/xxgk13/202012/t20201201_810752.html.

[14] The 2013 Action Plan authorized production restrictions during heavy-pollution alerts (Guofa [2013] No. 37, https://www.gov.cn/zwgk/2013-09/12/content_2486773.htm). The 2017 "2+26" plan required heating-season steel capacity cuts of 50% in Shijiazhuang, Tangshan, Handan, and Anyang, with staggered production elsewhere (https://www.mee.gov.cn/xxgk/hjyw/201703/t20170330_409037.shtml). The 2017–2018 autumn–winter plan required provinces to identify affected plants (https://www.mee.gov.cn/gkml/hbb/bwj/201708/t20170824_420330.htm). Tangshan began by halting half its sintering and pelletizing equipment (https://www.thepaper.cn/newsDetail_forward_1821404). The 2019 ultra-low-emission policy established phased steel-industry retrofit targets (Huan Daqi [2019] No. 35, https://www.mee.gov.cn/xxgk2018/xxgk/xxgk03/201904/t20190429_701463.html).

[15] The Beijing–Tianjin–Hebei alert criteria used forecast AQI above 200, with alert levels depending on the expected duration and severity of pollution (https://www.mee.gov.cn/gkml/hbb/bgth/201602/t20160204_329883.htm). The

Such restrictions could curtail sintering or ironmaking while leaving converters operational, allowing plants to partially offset reduced hot-metal production by increasing scrap use in converters.

3 Data and Empirical Strategy

3.1 Data

Our analysis combines firm-level production, environmental, financial, and scrap-purchase records with city-level Good-Air Days targets, air-quality data, and economic controls. The controls include annual GDP per capita and the share of employment in the secondary sector, both from the China City Statistical Yearbook. We describe the remaining data and their sources below.

Firm production, environmental, and financial records. The core data are firm-year records from the China Iron and Steel Association (CISA), which collects operating statistics from member steel producers.[16] The production and environmental records span 2001–2020 and cover firms subject to major pollution monitoring. The firms in our estimation sample produced 50% of China's crude steel in 2018.[17] For each firm-year, they report physical output of crude steel, pig iron, and sintering ore. The data also report SO_2 emissions, disaggregated by production stage (sintering, ironmaking, and total), together with environmental investment (total, air, and water). A separate CISA financial dataset, available from 2006, reports pre-tax profit per ton of crude steel, the main-business gross margin, aggregate net profit after income tax, operating revenue and cost, the wage bill per ton of crude steel, the annual wage per worker, construction in progress, and net fixed assets, and is merged to the production data by firm. Pre-tax profit per ton, the industry's standard gauge of profitability, and both wage measures are reported directly by CISA. By contrast, we construct operating revenue and cost per ton by dividing the corresponding firm-level totals by crude-steel output.[18]

We express all monetary outcomes in 2015 prices. Flow variables (pre-tax profit per ton, operating revenue and cost, aggregate net profit, both wage measures, and the firm-level scrap-price control) are deflated with the GDP deflator, and capital variables (environmental investment, construction in progress, and net fixed assets) with the fixed-asset investment price index.[19]

Blue Sky plan required emergency emission reductions of at least 10%, 20%, and 30% under yellow, orange, and red alerts, respectively, and called for process-specific emergency measures and seasonal production restrictions (Guofa [2018] No. 22, Article 28).

[16] CISA collects operating data from steelmakers with annual production exceeding 1 million tons. Its members are predominantly medium-sized and large producers, accounting for roughly 80% of China's crude-steel output (Brandt et al., 2022).

[17] Crude-steel output of the sample firms divided by national production as reported in *World Steel in Figures 2019* (see Section 2).

[18] The main-business gross margin is main-business revenue minus main-business cost, relative to main-business revenue.

[19] Both indices are constructed from National Bureau of Statistics data, chained, and normalized to 2015=100.

A third CISA source, an industry survey on metallic inputs, records the quantity and unit price of annual scrap purchases for a subset of producers. The survey does not report the converter scrap share itself. We instead construct purchased scrap per ton of crude steel as a proxy for this input-substitution margin.[20]

Because the CISA data are self-reported and aggregated to the firm level, two measurement issues arise. The first is misreporting. The main outcomes (crude steel, pig iron, sintering ore, and purchased scrap) are physical operating quantities tied to furnace throughput and material balances and cross-checked in industry reporting. They are therefore less susceptible to some measurement problems associated with financial variables, and they also avoid the confound in revenue-based performance measures documented for this industry (Li et al., 2026). Firm fixed effects further absorb time-invariant reporting differences. The second issue is aggregation. For multi-plant firms, a decline in the pig-iron-to-crude-steel ratio could reflect reallocation toward plants using less pig iron rather than a change in the input mix within individual plants. Two considerations mitigate this concern. First, sintering, ironmaking, and steelmaking are vertically integrated stages of the BF–BOF route (Brandt et al., 2022), with production capacities coordinated across stages. Substantial reallocation across plants would therefore require sufficient spare capacity at multiple stages or costly transfers of intermediate materials. Second, only a small number of matched firms operate plants in multiple cities, limiting the scope for cross-city production shifting in response to differential regulatory pressure, a concern related to the intra-firm pollution shifting documented by Gibson (2019) and Rijal and Khanna (2020).[21]

Policy targets and Good-Air Days. City-level Good-Air Days targets come from Kong and Liu (2024), who extract them from the 13th Five-Year Plans of municipal environmental protection bureaus. Annual counts of Good-Air Days (days with a daily AQI of 100 or below) come from Liu (2025), who compile daily AQI records from the China National Environmental Monitoring Center for 367 cities beginning in 2014.[22] We use the 2014–2015 average number of Good-Air Days as the baseline to smooth annual variation. For the 11 of our 54 sample cities without 2014 observations, we use the 2015 value.[23] Official plans instead use 2015 as the baseline for assessing

[20] After matching to the production panel, the scrap-purchase regression sample covers 17 firms and 59 firm-years, observed in 2012, 2014, 2016, and 2017.

[21] We examine plant locations using plant-level equipment records from the compliant-firm lists of China's Ministry of Industry and Information Technology (MIIT; Appendix Section C) and find that five of the 66 matched firms operate plants in more than one city. None is assigned to a Hebei city, which provides most of the identifying variation. Appendix Section C shows that the results are largely robust to excluding these firms and to assigning them a capacity-weighted average of their plant cities' target intensities.

[22] Official AQI statistics were available for a smaller set of cities before 2014, but Liu (2025) provides the earliest consistent city-level coverage used here. Self-reported city air-quality data were manipulated in the 2000s (Ghanem and Zhang, 2014), and the automation of monitoring stations in the mid-2010s substantially reduced such misreporting (Greenstone et al., 2022). Any remaining misreporting would affect the measured baseline and hence target intensity, but not our firm-level outcomes, which do not depend on reported air quality.

[23] Jiyuan, a provincially administered county-level city in Henan with one sample steel firm, is not covered by Liu

progress toward the 2020 targets.[24] For each prefecture-level city, we therefore observe the end-of-plan target, the 2014–2015 baseline average ($\overline{d}_c$), and the realized 2016–2019 average, which we use to validate the treatment measure and conduct robustness checks.

3.2 Key Variables

We describe three sets of key variables: target intensity, production outcomes, and environmental outcomes. The *target intensity* of firm i located in city c is the ratio of the city's end-of-plan Good-Air Days target to its 2014–2015 baseline, $T_{ic} = targetc/\overline{d}c$. Values above one indicate a required increase in Good-Air Days, with larger values corresponding to greater proportional improvements. Appendix Figure B1 maps this variation across the prefecture-level locations in the estimation sample.

Target intensity measures the improvement required of a city, regardless of whether it met its target. Cities with higher target intensity recorded larger gains in Good-Air Days over 2016–2019, both relative to baseline (defined as *realized improvement*) and in absolute days (columns (1) and (3) of Appendix Table A2; Appendix Figure B2). This relationship is concentrated among cities whose targets exceeded their baseline. For these cities, a one-unit increase in required proportional improvement is associated with 0.394 units of realized improvement, statistically significant at the 1% level. Among the 13 cities already meeting their targets at baseline, the distance above the target is unrelated to subsequent improvement. Column (2) of Appendix Table A2 reports these estimates. The positive relationship emerges in 2016 and remains statistically significant through 2020 (Appendix Figure B3). Because cities with poorer baseline air quality also had more room to improve, we interpret this relationship as suggestive rather than causal.

Our data do not report the converter scrap share directly, so we use the pig-iron-to-crude-steel ratio as our primary production outcome. A lower ratio is consistent with substituting scrap for pig iron per ton of crude steel; Section 4 derives an implied converter scrap share from this ratio. The sintering-to-crude-steel ratio measures upstream processing intensity, while purchased scrap per ton of crude steel provides more direct evidence of substitution in the scrap-reporting subsample. Section 4.1 discusses these measures in detail.

Abatement effort is measured by total environmental investment and by the component directed toward air-pollution control. For the emissions analysis, we use the source file's SO_2 measures by production stage and construct corresponding emissions-intensity measures. We winsorize the production ratios, output levels, and SO_2 measures at the 1st and 99th percentiles, and take natural

(2025). We assign it the Good-Air Days series of adjacent Jiaozuo, from which it was separated, and combine that series with Jiyuan's own end-of-plan target.

[24] See State Council, *The 13th Five-Year Plan for Ecological and Environmental Protection*, Table 1, https://www.mee.gov.cn/zcwj/gwywj/201811/t20181129_676583.shtml. Zhengzhou's official final evaluation likewise reports its 2015 value, 2020 target, and 2020 outcome; https://public.zhengzhou.gov.cn/D08Y/5904432.jhtml.

logs of the SO_2 measures to limit the influence of reporting outliers and estimate proportional changes.[25]

3.3 Sample Construction

We begin with the CISA production and environmental panel and impose five sample restrictions. First, we retain 2012–2019, providing four pre-treatment and four post-treatment years, with 2016 as the first treatment year (see the next subsection). This window also improves data comparability. Before 2012, the panel has more missing firm-year observations, and China's revised AQI-based air-quality reporting system was not yet in place.[26] We exclude 2020 because the COVID-19 shock disrupted steel production, transport, and local enforcement, introducing a separate source of post-treatment variation. Second, we retain firms whose principal product is crude steel to ensure comparable production ratios. Third, we exclude six specialty-steel producers that use electric arc furnaces (EAFs) rather than the BF–BOF route.[27] About one-third of the remaining firms with equipment records also operate EAFs alongside their converters, and Section 5.4 finds no evidence that this capacity drives the production response.

Fourth, we require at least seven firm-year observations per firm over 2012–2019, so that firm fixed effects are estimated from sufficiently long within-firm histories. Fifth, we drop one firm whose plant lies in one city's territory but which is administered by another city, so we cannot determine which city's target applies to it.[28]

We then assign Good-Air Days targets to firms based on their locations. China's cities are administratively nested, with prefecture-level cities encompassing smaller county-level cities; we therefore assign each firm the target published at the finest level available for its location. Economic controls are reported only at the prefecture level, so we use the corresponding parent-prefecture values for firms in county-level cities.[29] The estimation sample contains 70 firms and 546 firm-year observations across 54 cities but 55 distinct target locations, because the Suzhou firms lie in two county-level cities with different target intensities. Missing outcomes and the exclusion of firms

[25] Every non-missing SO_2 value is strictly positive, so logging drops no zero-valued observations and leaves each outcome's estimation sample unchanged.

[26] The Ministry of Environmental Protection issued the revised ambient air-quality standard (GB 3095–2012), on which the AQI is based, on February 29, 2012.

[27] We identify each firm's furnaces from the equipment records in MIIT's compliant-firm lists published in 2012–2014. Section 5.4 and Appendix Section C describe the data and the matching procedure.

[28] The firm, Tianjin Tiantie, has its plant in Handan, in Hebei Province, but is administered by Tianjin, a separate provincial-level municipality with its own, different Good-Air Days target.

[29] Four firms lie in county-level cities that carry their own targets. For one, the county and prefecture targets and baselines coincide, so the level of assignment is immaterial. The other three lie in county-level cities under Suzhou. Their county baselines differ from Suzhou's, but they share Suzhou's assigned target, which gives target intensities of 0.93 for the Changshu firm and 1.11 for the two Zhangjiagang firms, against 1.09 for the prefecture. Separately, Jiyuan is administered directly by Henan Province, so it has no prefecture-level parent and no entry in the prefecture-level city yearbook; its eight firm-year observations lack economic controls and drop from every regression.

that are alone in their province under province-by-year fixed effects leave 320–389 observations on 50–55 firms in the four main regressions.[30]

Appendix Table A3 reports summary statistics. The average firm produces 5.795 million tons of crude steel per year. Across firm-years, target intensity averages 1.237, so the average firm's city is required to achieve 23.7% more Good-Air Days than its baseline. It ranges from 0.767 to 2.091 across cities. Appendix Figure B5 plots the distribution of target intensity across target locations. Target intensity is highest in Hebei, where the major steel-producing cities had only 110–150 Good-Air Days on average in 2014–2015, compared with a target of 230.[31]

Table 1 compares firms in the bottom and top 30% of the target-intensity distribution before the policy. The two groups have similar city-level controls and outcomes, although pig iron per ton of crude steel is somewhat higher in the high-intensity group. Firm fixed effects absorb such baseline level differences. The split is only descriptive; the estimating equations use the full sample and continuous target intensity. Appendix Table A4 reports corresponding regression-based balance checks using continuous intensity and province fixed effects, including environmental investment, so the investment comparison starts from similar baselines.

Table 1: Baseline Characteristics by Target Intensity

	Low-intensity locations (bottom 30%) Mean (SD)	High-intensity locations (top 30%) Mean (SD)
Panel A. City controls		
GDP per capita (10,000 CNY)	5.29	6.18
	(2.55)	(3.01)
Secondary-sector employment share (percent)	49.03	50.44
	(15.65)	(8.51)
Panel B. Outcomes of interest		
Pig iron / crude steel	0.943	1.010
	(0.135)	(0.088)
Sintering / crude steel	1.525	1.559
	(0.377)	(0.352)
Crude steel output (10,000 tons)	482.7	529.5
	(340.4)	(402.5)
Total environmental investment (10,000 CNY, 2015 prices)	13,410	16,667
	(26,053)	(30,494)
Air-pollution investment (10,000 CNY, 2015 prices)	11,448	13,830
	(22,994)	(29,428)

Notes: Firm-year means for 2012–2015, with standard deviations in parentheses. Low- and high-intensity locations are the bottom and top 30% of the target-intensity distribution ($T_c \leq 1.016$ and $T_c \geq 1.213$), with 17 target locations each. Observations vary by row with outcome availability.

[30] Section 5 shows that the estimates are robust to using a common sample for all four regressions.

[31] Xingtai, Handan, Shijiazhuang, and Tangshan had baselines of 110, 126.5, 140, and 149.5 days, respectively. Chengde and Zhangjiakou, the other two Hebei locations in the sample, already exceeded the target at baseline.

3.4 Research Design

As described in Section 2, the 13th Five-Year Plan Outline established the share of Good-Air Days in prefecture-level cities as a binding indicator in March 2016. The State Council's environmental protection plan, issued in November 2016, reaffirmed this indicator, while city-specific targets were set in local 13th Five-Year Plans released at different dates.[32] Because these targets applied to the entire planning period despite differences in announcement dates, we treat 2016, the first year of the plan, as the start of treatment.

We compare steel firms in cities required to achieve larger proportional improvements in Good-Air Days with firms in cities facing smaller required improvements within the same province, before and after implementation began in 2016. Because every city received a target, there is no untreated group. Instead, we exploit differences in this required improvement, measured by target intensity (Section 3.2), which depends on both the city's end-of-plan target and its baseline air quality. The targets were not tied to a single policy instrument. As discussed in Section 2, local governments could pursue them through production restrictions, tighter emission standards, inspections, and other measures. Target intensity therefore measures the overall regulatory pressure a city faced, not exposure to any one of these instruments. Cities that already met their end-of-plan targets at baseline have intensity below one, indicating lower but not necessarily zero regulatory pressure. The plan required even cities meeting air-quality standards to "strengthen protection and continue to improve."[33] Our baseline retains the continuous intensity measure without imposing a threshold below which regulatory pressure disappears. Section 5 considers an alternative that sets target intensity to one for cities already meeting their targets.

The identifying assumption is that, absent the Good-Air Days target regime, firms located in higher- and lower-intensity cities within the same province would have followed similar outcome trends from the pre-plan period (2012–2015) through the plan period (2016–2019). This assumption does not require random assignment of targets. Instead, it requires that, conditional on province-by-year fixed effects and city controls, target intensity be unrelated to the outcome trends that firms would have followed in the absence of the policy.

3.5 Estimating Equations and Identification

Specification. We assess the plausibility of parallel trends over the pre-treatment period with an event-study framework. Equation (1) presents the specification, with 2015, the last pre-plan year,

[32] State Council, Guofa [2016] No. 65, https://www.gov.cn/gongbao/content/2016/content_5148753.htm.

[33] State Council, *The 13th Five-Year Plan for Ecological and Environmental Protection*, Chapter 4, Section 1, https://www.mee.gov.cn/zcwj/gwywj/201811/t20181129_676583.shtml.

as the omitted reference year:

$$Y_{ict} = \sum_{\tau \neq 2015} \beta_\tau \left(T_{ic} \times \mathbf{1}(t = \tau) \right) + \mathbf{X}'_{ct}\gamma + \alpha_i + \delta_{pt} + \varepsilon_{ict} \tag{1}$$

Y_{ict} is the outcome of interest for firm i in city c and year t, and p indexes the province containing city c. The target intensity measured for firm i through its city is $T_{ic} = \textit{target}_c/\overline{d}_c$, the ratio of city c's end-of-plan Good-Air Days target to its 2014–2015 baseline. The indicator function $\mathbf{1}(t = \tau)$ equals one when $t = \tau$, and each β_τ captures the differential change in the outcome from 2015 to year τ associated with a one-unit increase in target intensity. The vector $\mathbf{X}_{ct}$ includes time-varying city controls: per-capita GDP and the secondary-sector employment share. Firm fixed effects, α_i, absorb time-invariant firm characteristics. Province-by-year fixed effects, δ_{pt}, absorb province-specific shocks and policies in each year, including regulatory changes and regional business cycles, so that these are not attributed to target intensity. The error term is ε_{ict}. We cluster standard errors at the city level. Appendix Section C reports province-clustered standard errors and wild-cluster bootstrap inference.

The baseline estimating equation replaces the year-specific interactions in Equation (1) with a single post-treatment indicator:

$$Y_{ict} = \beta \left(T_{ic} \times \textit{Post}_t \right) + \mathbf{X}'_{ct}\gamma + \alpha_i + \delta_{pt} + \varepsilon_{ict} \tag{2}$$

where $\textit{Post}_t = \mathbf{1}(t \geq 2016)$, and all remaining notation follows Equation (1). The coefficient of interest, β, captures the differential post-implementation change in the outcome associated with a one-unit increase in target intensity. The coefficient therefore reflects the combined response to this pressure, not the effect of any single measure.

Identifying variation. Our fixed-effects specification has two implications. First, identification comes from provinces with multiple sample cities. In single-city provinces, the interaction between target intensity and Post is absorbed by province-by-year fixed effects, while provinces with only one firm are excluded as singletons. We accept this restriction to avoid attributing province-specific shocks or trends to target intensity. Second, because cities within a province usually received the same target, province-by-year fixed effects absorb most variation in target levels.[34] Identification therefore comes mainly from differences in baseline Good-Air Days: for a common target, fewer baseline days imply a larger required proportional improvement. Our estimates capture responses to these differences in required improvement, rather than the effect of assigning different targets to cities with the same baseline air quality. Alternative measures based on target–

[34] In the estimation sample, 14 of 26 provinces contribute a single city, and 11 of the remaining 12 provinces assign the same target to all sample cities. Hubei is the exception, with targets of 266 days for Ezhou and 296 for Huangshi.

baseline gaps or realized improvements largely reflect the same underlying baseline air-quality variation and do not provide independent identifying variation.

Identification concerns. The main concern is that firms in cities with different baseline air quality might have followed different outcome trends even without the policy. Because the specification includes province-by-year fixed effects, such a trend would have to differ across cities within the same province and change in 2016. Cities with unusually poor air quality in 2014–2015 might have improved regardless, with their steel producers adjusting for reasons unrelated to the targets. We assess this concern using the event-study framework introduced above. As a complementary check, Appendix Table A4 shows that target intensity is not significantly correlated with pre-treatment outcome levels, conditional on province fixed effects. Appendix Figure B4 illustrates this relationship for the pig-iron-to-crude-steel ratio. A second concern is concurrent city-specific policies. Province-by-year fixed effects do not absorb interventions such as the "2+26" winter controls, which targeted heavily polluted cities in northern China and could be correlated with target intensity. Section 5.3 examines these policies. Treatment begins in 2016 in every city, so the design has no staggered timing to separate the targets from other changes in that year. It relies on differences in required improvement within a province, and Section 5 uses the 14 locations that had already met their targets as a comparison group.

4 Main Results

This section examines how firms respond to greater regulatory pressure, measured by target intensity. We begin with production adjustments, using the pig-iron-to-crude-steel and sintering-to-crude-steel ratios, followed by purchased scrap per ton of crude steel as a more direct check on input substitution. We then examine environmental investment. For both production ratios and environmental investment, we present event-study estimates before reporting the difference-in-differences results from Equation (2).

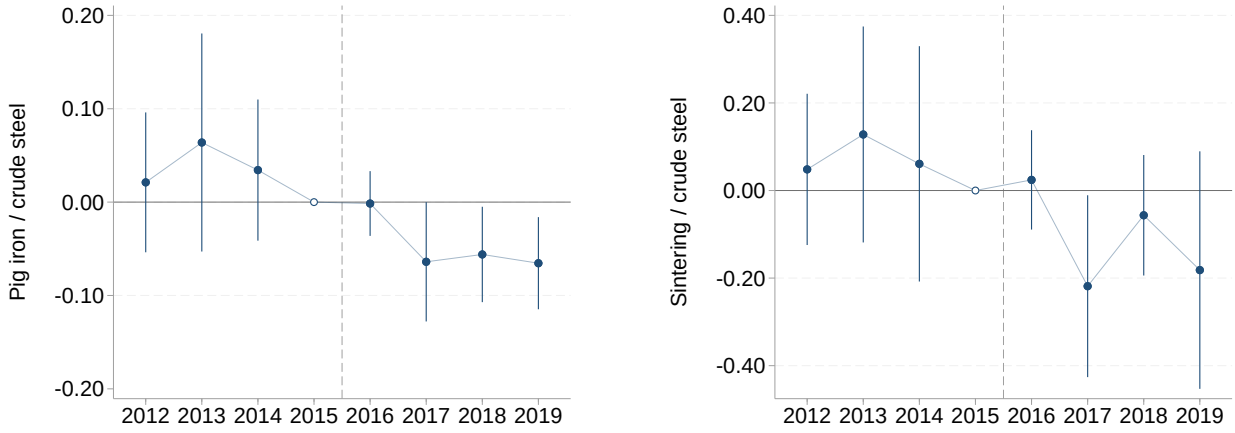
4.1 Production Process

Event-Study Estimates

Figure 2 presents the event-study estimates for the pig-iron-to-crude-steel and sintering-to-crude-steel ratios. The pre-treatment coefficients are statistically insignificant for both ratios, providing no evidence of differential trends before 2016. The 2016 estimates are close to zero, suggesting that production adjustments took time to emerge. The decline begins in 2017, and the pig-iron-to-crude-steel coefficients remain negative through 2019. The sintering-to-crude-steel coefficients are also negative in every year from 2017 to 2019, although less precisely estimated.[35] The sintering-to-pig-iron ratio shows no statistically significant response in any year, and its pooled estimate is

[35] We cannot reject equality of these coefficients across 2017–2019 ($p = 0.315$).

small relative to its mean, consistent with sintering broadly tracking pig-iron production (Appendix Table A5). Because the response is limited in 2016, the pooled difference-in-differences estimates may understate the magnitude of the adjustment in subsequent years.



(a) Pig iron / crude steel

(b) Sintering / crude steel

Figure 2: Event-Study Results: Production Ratios. *Notes*: The y-axis reports the coefficients β_τ estimated from equation (1). The omitted year is 2015, and the vertical dashed line marks the start of the post-treatment period. Vertical lines denote city-clustered 95% confidence intervals. Regressions include firm and province-by-year fixed effects and city-level controls.

Difference-in-Differences Estimates

Table 2 reports the difference-in-differences estimates from Equation (2). Column (1) of Table 2 shows that firms facing more demanding targets use less pig iron per ton of crude steel. A one-standard-deviation increase in target intensity (0.301) reduces this ratio by 0.023, or 2.4% of its mean, statistically significant at the 5% level. Because pig iron and scrap are the main metallic inputs to the converter, this decline implies greater use of scrap relative to pig iron. Column (2) indicates that firms also significantly reduce sinter per ton of crude steel. A one-standard-deviation increase in target intensity reduces sinter per ton of crude steel by 3.5% of its mean, consistent with less upstream ore processing. Column (3) of Table 2 finds no statistically significant change in crude-steel output.[36] Together, these results suggest that firms adjusted their input mix rather than reducing steel production. This contrasts with the temporary reductions in operating hours and output documented by Liu et al. (2027) among Chinese firms responding to short-term political incentives.

The pig-iron-to-crude-steel ratio has a direct technological interpretation. The converter's metallic charge consists mainly of pig iron plus scrap, and crude steel output is that charge net

[36] In logs, crude-steel output changes by -0.061 per unit of target intensity, which is not statistically significant.

of yield losses:

$$RS = \eta\,(PI + S) \tag{3}$$

where *RS*, *PI*, and S denote crude steel, pig iron, and scrap in tons, and η is the converter yield. The accounting relationship implies that the scrap share of the converter's metallic charge, $\sigma \equiv S/(PI + S)$, equals $1 - \eta\,\rho$, where $\rho = PI/RS$ is the pig-iron-to-crude-steel ratio. We calibrate η by regressing crude-steel output on the sum of pig-iron output and purchased scrap through the origin, obtaining $\eta = 0.977$ (standard error 0.005) from 130 firm-year observations.[37]

We construct the implied converter scrap share σ for each firm-year and re-estimate Equation (2) with it as the outcome. The implied share averages 7.8% in our sample. Column (4) of Table 2 shows that a one-standard-deviation increase in target intensity raises this share by 2.2 percentage points. This is a linear transformation of the estimate in column (1) of Table 2, not independent evidence: because $\sigma = 1 - \eta\rho$, the coefficient on σ equals $-\eta$ times the coefficient on ρ.[38]

For context, the converter scrap share among China's BF–BOF producers rose from about 7% in 2016 to 16% in 2020, an increase of 9 percentage points (Shangguan et al., 2024). Our estimate of 2.2 percentage points per standard deviation of target intensity is roughly one-quarter as large as this increase. Because our estimate captures within-province differences across cities, whereas the national figure reflects an aggregate trend, this comparison serves only to illustrate the magnitude.

Evidence from Purchased Scrap

The production ratios examined above suggest that firms substitute scrap for pig iron in converters. We use firm-level scrap-purchase data matched to our panel to provide more direct evidence of this substitution, measuring purchased scrap per ton of crude steel because the data do not report the converter scrap share directly.[39] Three components can create discrepancies between purchased scrap and scrap actually charged into converters: purchased scrap held in inventory, home scrap

[37]The calibration uses all firm-years in the scrap survey with complete purchase records, a wider sample than the scrap-reporting regression subsample used below. It uses pig-iron output and purchased scrap in place of the converter's actual metallic charge, omitting home scrap and potentially including pig iron sold, cast, or inventoried rather than charged into converters, as well as scrap used outside the converter. The estimated yield exceeds the roughly 90% metallic yield typical of converter operation (Voraberger et al., 2022), consistent with unobserved home scrap entering the charge. Interpreting the implied scrap share requires these measurement differences not to change differentially with treatment. By the same identity, $\sigma = \eta(S/RS)$, the form used with the purchased-scrap measure below.

[38]The estimated increase ranges from 2.05 to 2.28 percentage points as η varies from 0.90 to 1.00. The constructed share is negative for 84 of 389 firm-years (22%), when reported crude-steel output falls below η times reported pig-iron output. This can occur when pig iron is sold, cast, or inventoried rather than charged into converters. We retain these observations because excluding them would select on the outcome, although they lower the average implied share relative to a converter-level measure.

[39]Crude steel, the converter's output, measures production scale. Pig iron is less suitable as a denominator: some may be sold, cast, or inventoried rather than charged into converters, and its output per ton of crude steel falls with target intensity.

Table 2: Good-Air Days Target Intensity and Steel Production

Dependent variable	(1) Pig iron/ crude steel	(2) Sintering/ crude steel	(3) Crude-steel output	(4) Implied converter scrap share
Units	Tons/ton	Tons/ton	10k tons	Percent
Target intensity × Post	-0.076**	-0.166*	11.072	7.411**
	(0.031)	(0.099)	(23.432)	(3.061)
Observations	389	364	436	389
R^2	0.800	0.800	0.981	0.800
City controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes
Dep. var. mean	0.944	1.446	579.5	7.770

Notes: Each column reports a continuous difference-in-differences estimate from Equation (2). Column (4) is the implied converter scrap share defined in Section 4. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

generated and recharged internally, and purchased scrap used outside the converter. Firm fixed effects absorb stable firm-specific differences in these components relative to crude-steel output. Interpreting the proxy as evidence of substitution requires that these components do not change differentially with target intensity.

Purchased scrap per ton of crude steel increases with target intensity. Column (1) of Appendix Table A6 indicates that a one-standard-deviation increase in target intensity raises purchased scrap by approximately 20.4 kg per ton of crude steel ($p < 0.1$), equivalent to 29% of the subsample mean of 70.1 kg/ton.[40] Column (2) uses purchased scrap per ton of pig iron instead and also yields a positive coefficient, although less precisely estimated.

Equation (3) and the coefficient in column (1) of Appendix Table A6 imply that a one-standard-deviation increase in target intensity raises the purchased-scrap share of the metallic charge by 2.0 percentage points in the scrap subsample, close to the 2.2 percentage points implied by the pig-iron-to-crude-steel ratio in column (4) of Table 2.[41] The two estimates draw on separate CISA files, one reporting stage-level production and the other scrap purchases, so their agreement is not mechanical.

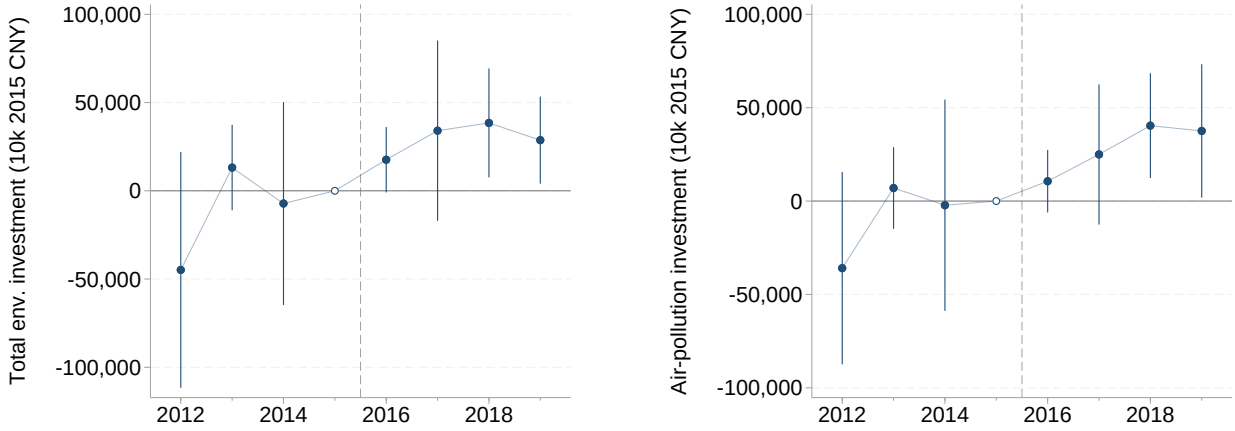
[40]Target intensity varies less within the scrap subsample than in the main sample (standard deviation 0.152 versus 0.301), because the 17 scrap-reporting firms are concentrated in fewer cities. We therefore scale the estimates by the subsample standard deviation.

[41]The share is the coefficient in column (1) of Appendix Table A6 times the subsample standard deviation of target intensity times η: $0.134 \times 0.152 \times 0.977 \approx 2.0$ percentage points. Because the conversion only multiplies the coefficient in column (1) of Appendix Table A6 by constants, it has the same significance and sample as that column ($p < 0.1$, 59 observations).

4.2 Environmental Investment

Event-Study Estimates

Figure 3 presents the event-study estimates for total and air-pollution environmental investment. The pre-treatment coefficients are statistically insignificant, and the post-treatment coefficients are positive in every year from 2016, rise through 2018, remain positive in 2019, and are significant at the 5% level in 2018 and 2019 for both measures.



(a) Total environmental investment

(b) Air-pollution investment

Figure 3: Event-Study Results: Environmental Investment. *Notes*: The y-axis reports the coefficients β_τ estimated from equation (1), measured in 10,000 CNY at 2015 prices. The omitted year is 2015, and the vertical dashed line marks the start of the post-treatment period. Vertical lines denote city-clustered 95% confidence intervals. Regressions include firm and province-by-year fixed effects and city-level controls.

Difference-in-Differences Estimates

Columns (1) and (2) of Table 3 show that environmental investment rises with target intensity. After 2015, a one-standard-deviation increase in target intensity raises total environmental investment by about 117 million CNY at 2015 prices, or 49% of the sample mean, and air-pollution investment by about 109 million CNY, or 56% of its mean. Both estimates are statistically significant at the 1% level.[42] Water-pollution investment shows no significant change (column (3)). Column (4) indicates that the composition of environmental investment shifts toward air-pollution control. A one-standard-deviation increase in target intensity raises the air share of environmental investment by 5.6 percentage points from a mean of 79%, statistically significant at the 5% level, while the water share in column (5) does not change significantly.

[42] Given the highly skewed distribution of environmental investment, we also estimate both outcomes using Poisson pseudo-maximum likelihood. The estimates remain positive and statistically significant at the 1% level (Panel B of Appendix Table C1).

Table 3: Good-Air Days Target Intensity and Environmental Investment

Dependent variable	(1) Total env. investment	(2) Air-pollution investment	(3) Water-pollution investment	(4) Air invest. share	(5) Water invest. share
Units		10k 2015 CNY		Share	Share
Target intensity × Post	38,997***	36,089***	-4,719	0.188**	-0.172
	(13,677)	(13,197)	(4,137)	(0.075)	(0.174)
Observations	338	320	156	320	156
R^2	0.584	0.575	0.744	0.537	0.577
City controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	24,039	19,511	4,542	0.788	0.207

Notes: Each column reports a continuous difference-in-differences estimate from Equation (2). Columns (4)–(5) are the shares of environmental investment spent on air- and water-pollution control. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5 Robustness Checks

This section examines whether our estimates depend on the timing and sample, the measure of target pressure, concurrent policies, shifts toward electric arc furnaces, influential provinces, or the method of inference. Where a check covers both, we report the production ratios before environmental investment.

5.1 Timing and Sample

Firms in cities with more demanding targets may already have been reducing pig-iron use and increasing environmental investment before 2016. To assess this concern, we assign a placebo policy date of 2014 and re-estimate the model using only the pre-policy years 2012–2015. Panel A of Appendix Table A7 reports statistically insignificant estimates for all four outcomes, providing no evidence of differential pre-policy trends. We also examine whether the findings are driven by 2019, when ultra-low-emission retrofit requirements for steel were introduced. Panel B shows that all four estimates remain statistically significant when 2019 is excluded.

If firms facing more demanding targets were also more likely to exit the panel or stop reporting, our estimates could reflect a selected sample of survivors. Panel C of Appendix Table A7 relaxes the baseline requirement of at least seven observed years to six. The investment estimates remain positive and significant and the production-ratio estimates remain negative, although the pig-iron-to-crude-steel estimate is no longer statistically significant. Appendix Table A8 shows that target intensity does not significantly predict exit before 2018, inclusion under the seven-year rule, or

outcome reporting after 2015. Appendix Section C also reports estimates for all four outcomes on a common sample. Together, these checks suggest that sample selection and differential reporting are unlikely to drive our findings.

5.2 Measuring Target Pressure

Target intensity measures the proportional improvement in Good-Air Days required of each city. The regulatory pressure firms faced may also depend on local enforcement effort, which realized improvement partly reflects, or on the absolute number of additional days needed to meet the target. Panel A of Appendix Table A9 replaces target intensity with realized improvement, while Panel B uses the gap between the target and baseline. All estimates retain their baseline signs and are statistically significant except the sintering-to-crude-steel estimate under the gap measure. The investment estimates under realized improvement are significant at the 10% level. Overall, the results are broadly robust to these alternative measures.

Measurement error in the targets from Kong and Liu (2024), which come from municipal 13th Five-Year Plans, could attenuate our estimates. We therefore use alternative city-specific targets published in provincial and municipal documents, changing the target for 22 of the 55 locations. Appendix Table A10 lists the sources. Panel A of Appendix Table A11 reports larger estimates in magnitude than the baseline for all four outcomes, significant at the 5% level except the sintering-to-crude-steel estimate, which is significant at the 10% level. Appendix Section C reports similar results when restricting the sample to cities with documented targets. The larger estimates are consistent with measurement error attenuating the baseline responses.

Target intensity is below one for the 14 locations that already met their targets at baseline, so the baseline specification assigns less pressure to locations farther above their targets. Setting their target intensity to one yields per-standard-deviation effects similar to the baseline and statistically significant, as reported in Panel A of Appendix Table A12. Because continuous-treatment two-way fixed-effects estimates are difficult to interpret as average treatment effects (Callaway et al., forthcoming), we also compare terciles of target intensity with these attaining locations, as detailed in Appendix Section C. Appendix Figure B6 shows that the pig-iron-to-crude-steel response is largest and statistically significant in the highest tercile. The sintering-to-crude-steel point estimate is also largest in the highest tercile but is not statistically significant. These results suggest stronger production adjustments under more demanding targets and indicate that the findings are not driven by how attaining locations are treated.

5.3 Concurrent Policies

Province-by-year fixed effects absorb the effects of most clean-air and steel-sector policies during the 13th Five-Year Plan (2016–2020), which were set nationally or at the provincial level, as listed

in Appendix Table A1. We therefore focus on policies that varied across cities within provinces, particularly the "2+26" program, which imposed stricter winter air-pollution controls on Beijing, Tianjin, and 26 surrounding cities in northern China during the post-treatment period. If these cities also faced more demanding Good-Air Days targets, our estimates could partly capture responses to the winter controls. Panel A of Appendix Table A13 controls for "2+26" exposure, while Panel B excludes the 28 cities. In both panels, the production-ratio estimates in columns (1) and (2) remain negative, statistically significant, and larger in magnitude than the baseline estimates. In contrast, the investment estimates in columns (3) and (4) fall to between 6% and 44% of their baseline magnitudes and lose statistical significance. Appendix Section C details which firms contribute identifying variation inside and outside the region. These results indicate that the input-mix response extends beyond the winter-control region, whereas the investment response is concentrated where winter controls overlapped with the Good-Air Days targets.

The post-treatment period overlaps with the national steel supply-side reform, whose capacity-reduction quotas may have differed across cities within provinces. Because quota allocations likely depended on local steelmaking capacity, we interact year indicators with each city's pre-policy crude-steel output, a proxy for capacity.. Appendix Table A14 shows that the estimates change little. The 2017 ban on induction furnaces lowered scrap prices nationally, potentially encouraging scrap substitution. Province-by-year fixed effects absorb common price shocks within provinces, while Appendix Section C reports no statistically significant relationship between target intensity and the prices firms paid for purchased scrap. The pig-iron-to-crude-steel response also persists when 2017 is excluded. These checks indicate that concurrent industrial policies are unlikely to fully explain the stronger production responses in cities with more demanding targets.

5.4 Electric-Arc-Furnace Production

An alternative explanation for the declining production ratios is that firms shift production toward electric arc furnaces (EAFs) rather than use more scrap in their existing converters. We match furnace-level equipment records published by MIIT between 2012 and 2020 to 66 of the 70 sample firms, as described in Appendix Section C. About one-third of the matched firms also operated EAFs before the policy. If firms shift production toward existing EAF capacity, both production ratios should fall more among these firms. However, Appendix Table A15 shows no statistically significant differential response for either ratio ($p = 0.667$ and $p = 0.311$). These results indicate that a shift toward EAF production is unlikely to explain the observed production-ratio declines.

5.5 Influential Provinces and Inference

If the estimated responses are driven by a few provinces, they may not reflect a broader pattern. Column (5) of Appendix Table A16 shows that four provinces account for nearly all the identify-

ing variation, with Hebei contributing most, followed by Shandong. Excluding each province in turn leaves all production-ratio estimates negative and both investment estimates positive and statistically significant. Without Hebei, the pig-iron-to-crude-steel estimate of -0.084 remains close to the baseline but is imprecise, while the sintering-to-crude-steel and investment estimates become larger and remain statistically significant. Appendix Section C reports results for the other provinces and alternative inference methods. Under the city-level wild bootstrap, both investment estimates remain significant at the 5% level and the pig-iron-to-crude-steel estimate at the 10% level. None is significant under the province-level bootstrap, which has only 12–14 clusters. The direction of the estimates is robust to dropping any single province, whereas their statistical significance is sensitive to clustering at the province level.

In addition to the checks above, we examine whether differential trends by baseline firm and city characteristics affect the results. Allowing separate year effects by baseline firm size, pollution intensity, ownership, and city income leaves the pig-iron-to-crude-steel and investment estimates close to the baseline and statistically significant. Appendix Section C provides details.

6 Heterogeneous Responses

The average responses may mask heterogeneity across firms in the costs and scope for production adjustment and end-of-pipe abatement. Firm ownership may shape how firms comply because state-owned and private firms face different abatement costs (Fan et al., 2025b). In the steel industry, private firms face higher financing costs than state-owned firms (Brandt et al., 2022). State-owned firms may therefore be better positioned to finance capital-intensive abatement, while private firms may rely more on adjusting production with existing equipment. Firm size may also matter. Large firms operate larger blast furnaces,[43] which are more costly to shut down and restart (Brandt et al., 2022). They may therefore reduce pig iron per ton of crude steel by less than smaller firms, while their scale may make environmental investment easier to finance. Beyond these cost differences, firms may also differ in their scope for adjustment. Firms with higher pre-policy pollution intensity may have more room to reduce emissions and adjust along both margins. Similarly, firms using less scrap before the policy may have more room to increase the scrap share because they are further from the converter's heat-balance limit.

We estimate these differences with a triple-interaction difference-in-differences specification:

$$Y_{ict} = \beta_1 \left(T_{ic} \times \mathit{Post}_t\right) + \beta_2 \left(T_{ic} \times \mathit{Post}_t \times D_i\right) + \mathbf{X}'_{ct}\gamma + \alpha_i + \delta_{pt} + \varepsilon_{ict} \tag{4}$$

where D_i is a binary firm characteristic. The coefficient β_1 measures the treatment effect for the

[43] In the MIIT equipment lists (Appendix Section C), the median largest blast furnace is 2,500 m^3 among large firms and 1,080 m^3 among smaller firms.

reference group, and β_2 captures the differential effect for firms with $D_i = 1$. Detailed estimates are reported in Appendix Tables A17–A20.

Production margin. Private firms reduce both production ratios more than state-owned firms, whose estimates are close to zero and statistically insignificant. Panel A of Appendix Table A17 reports that the private–SOE differential is significant at the 1% level for pig iron per ton of crude steel and at the 10% level for sintering per ton of crude steel. Firm size matters as well. Large firms, defined as those above the sample median of pre-2015 crude-steel output, reduce pig iron per ton of crude steel less than smaller firms, with a differential significant at the 1% level (Panel A of Appendix Table A18). The difference for sintering is not statistically significant. Because most private firms in the sample are smaller firms, the ownership and size comparisons largely overlap. Panel A of Appendix Table A19 finds no statistically significant differences in either production ratio by pre-policy pollution intensity. Columns (1)–(2) of Appendix Table A20 report similar results for baseline scrap use, measured by the 2012–2014 pig-iron-to-crude-steel ratio.

Investment margin. The investment response does not differ significantly by firm ownership or size. Panel B of Appendix Tables A17 and A18 shows that both total and air-pollution investment increase across all groups, with estimates statistically significant at least at the 10% level. Contrary to expectations, heavier polluters increase total environmental investment less than lighter polluters, and Panel B of Appendix Table A19 reports that this difference is significant at the 5% level, while the difference in air-pollution investment is not statistically significant. One possible explanation is that heavier polluters had already installed much of their abatement equipment under the 2013 Action Plan, before the targets took effect (see Section 7.1). Columns (3)–(4) of Appendix Table A20 further indicate that the investment response does not differ significantly by baseline scrap use.

7 Further Discussion: Reported Emissions and Firm Performance

Emissions and financial performance are commonly used to evaluate environmental regulation and are routinely reported by regulators and firms. Having documented firms' adjustments in production and environmental investment, we now examine these outcomes for the same firms. Reported SO_2 emissions indicate whether the input-mix adjustment is reflected in official emissions records, while pre-tax profit per ton measures firms' financial performance as they adjust.

7.1 Reported SO_2 Emissions

We examine reported SO_2 per ton of crude steel, total SO_2, and SO_2 from sintering. Figure 4 presents the event-study estimates. For all three measures, the 2012 and 2013 coefficients are positive and statistically significant, and the post-2015 coefficients are negative but not statisti-

cally significant. The SO_2 gap between firms in higher- and lower-intensity cities opened between 2013 and 2015, before the targets took effect, and did not widen significantly afterwards. Its timing coincides with the 2013 Air Pollution Prevention and Control Action Plan, which required desulfurization equipment on sintering machines;[44] firms in the dirtiest cities, which later faced the highest target intensity, plausibly had the most to install. Appendix Table A21 reports the pooled difference-in-differences estimates for the three measures. All three are negative, but the event studies show that they mostly reflect the decline before the targets took effect, so we do not attribute them to the Good-Air Days targets.

Appendix D quantifies the reduction in reported SO_2 implied by the observed input substitution, assuming that SO_2 emissions per ton of sinter after end-of-pipe treatment remain constant. The reduction in pig iron per ton of crude steel implies a reduction of approximately 1.9% in reported SO_2 relative to its pre-policy mean; applying the same assumption directly to the estimated reduction in sinter per ton of crude steel gives approximately 2.9%. These calculations are illustrative rather than estimates of the causal effect on emissions. They suggest that the production adjustment would generate a small additional reduction in reported SO_2, which the pre-existing differential trends and the imprecision of the event-study estimates prevent us from isolating.

The reduction in reported SO_2 could be smaller still. Our data record SO_2 released after end-of-pipe treatment rather than SO_2 generated upstream of it,[45] and flue-gas desulfurization was already widespread on sintering machines before the Good-Air Days targets.[46] Desulfurization requires costly inputs, including reagents and electricity, whose use depends on pollution loads and treatment requirements (Ministry of Environmental Protection, 2016; Cui et al., 2021). If emissions constraints bind and abatement equipment can be operated at varying intensity, a lower load entering treatment equipment may allow firms to run it less intensively while remaining compliant.[47] Emissions per ton of sinter after end-of-pipe treatment may then rise, so the calculation above may overstate the reduction in reported SO_2, and part of the gain from input substitution may take the form of lower treatment costs. This possibility differs from the increase in environmental in-

[44] State Council, *Air Pollution Prevention and Control Action Plan*, Guofa [2013] No. 37, September 10, 2013; https://www.gov.cn/zwgk/2013-09/12/content_2486773.htm.

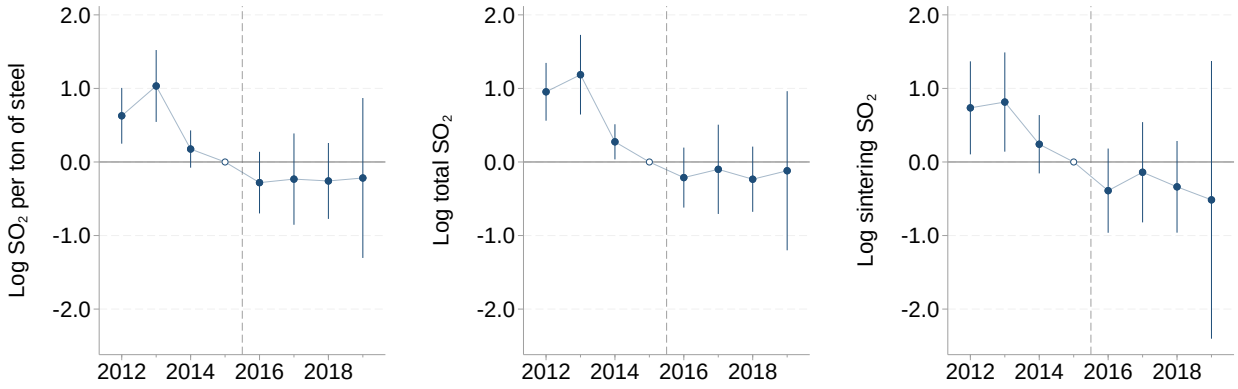
[45] The self-monitoring guidelines distinguish measurements at discharge outlets, which concern pollutants released to the environment, from measurements within pollution-control facilities, which can characterize pollution loads entering treatment equipment. See Ministry of Environmental Protection of China, *Self-Monitoring Guidelines for Pollution Sources: General Rule* (HJ 819-2017), and *Self-Monitoring Guidelines for Pollution Sources: Iron and Steel Industry and Coking Chemical Industry* (HJ 878-2017).

[46] According to China's Ministry of Environmental Protection (2015), sintering machines equipped with flue-gas desulfurization facilities accounted for 88% of China's total sintering-machine area by the first half of 2015. Source: Ministry of Environmental Protection, *Report on Major Pollutant Emissions in the First Half of 2015*, September 6, 2015, https://www.mee.gov.cn/gkml/sthjbgw/qt/201509/t20150906_309369.htm.

[47] Evidence suggests that the use of installed controls can change in the short run. For example, Zhang et al. (2025) attribute higher particulate emissions at U.S. coal plants to temporarily reduced end-of-pipe control while inspections lapsed during the 2018–19 federal government shutdown.

vestment documented in Section 4: investment measures capital expenditure, whereas operating intensity concerns how installed equipment is run. Our data do not separately identify desulfurization operating costs or removal rates, so we cannot test this mechanism directly.

SO_2 also rarely determines whether a day counts as a Good-Air Day. In 2017 it was the primary pollutant on fewer than 0.1% of the days on which the 74 key cities exceeded the air-quality standard, against 47.0% for $PM_{2.5}$, and on none of the exceedance days in the Beijing–Tianjin–Hebei region.[48] Sintering is the industry's largest source of $PM_{2.5}$ (Section 2), so less sinter per ton of crude steel would lower emissions of the pollutant that most often decides Good-Air Days. Reported SO_2 is therefore a poor yardstick for the production adjustment: the production ratios date the adjustment to 2017, whereas the SO_2 data would suggest an earlier response.



(a) SO_2 per ton of crude steel **(b)** Total SO_2 **(c)** Sintering SO_2

Figure 4: Event-Study Results: Log SO_2 Emissions. *Notes*: The y-axis reports the coefficients β_τ estimated from equation (1) with the log outcomes of Appendix Table A21. The omitted year is 2015, and the vertical dashed line marks the start of the post-treatment period. Vertical lines denote city-clustered 95% confidence intervals. Regressions include firm and province-by-year fixed effects and city-level controls.

7.2 Firm Performance

We next examine whether these adjustments coincide with lower profitability. This question speaks to the long-standing debate over whether environmental regulation imposes costs on firms or encourages efficiency-enhancing innovation and process change (e.g., Porter and van der Linde, 1995; Jaffe and Palmer, 1997; Berman and Bui, 2001; Lanoie et al., 2011; Ambec et al., 2013; Cohen and Tubb, 2018). We use matched financial records, which cover primarily listed firms. The post-policy period also coincides with a sharp recovery in the steel market and China's supply-side

[48] Ministry of Ecology and Environment, *2017 China Ecological and Environmental Status Bulletin*, section on ambient air quality; https://www.cnemc.cn/jcbg/zghjzkgb/201905/P020190529486578089674.pdf.

reform.[49] Our analysis documents how these firms' profitability changes as they adjust production and invest in end-of-pipe abatement.

Pre-tax profit per ton of crude steel, as reported by CISA, rises with target intensity in column (1) of Table 4. A one-standard-deviation increase in target intensity is associated with roughly 73 CNY more per ton after 2015 ($p < 0.01$), or 56% of the unusually low sample mean of 130 CNY per ton. Relative to operating revenue per ton, a more stable benchmark, the increase is about 1.3%. The main-business gross margin, which averages 9.2% in the sample, rises by 2.0 percentage points (column (2), $p < 0.01$). Aggregate net profit after income tax has a positive point estimate of about 519 million CNY (column (3), $p < 0.1$).[50]

Pre-tax profit per ton and the main-business gross margin are particularly exposed to the 2016–2019 steel-market recovery and the 2017 induction-furnace ban. Panel (a) of Appendix Figure B7 shows that the pre-treatment coefficients for pre-tax profit per ton are statistically insignificant, while the post-treatment coefficients are positive in every year and largest in 2017 and 2018. In Panel (b) of Appendix Figure B7, the 2014 coefficient for the main-business gross margin is already positive and statistically significant. We therefore treat the gross-margin results as supporting evidence rather than the primary evidence on profitability.

Appendix Table A22 reports timing and sample robustness checks suggesting that neither the induction-furnace ban nor the inclusion of particular years or provinces fully explains the financial gains. Excluding 2017 leaves both estimates close to baseline, and splitting the post-period shows both already improving in 2016, before the ban, and strengthening thereafter. Excluding 2015, when steel prices bottomed, also leaves both estimates close to baseline, so an unusually poor base year does not explain the gains either. Without 2017 and 2018 the profit estimate is lower but still positive and significant, and it stays positive when each of the three provinces that identify it is dropped in turn, although it nearly triples without Hebei.[51] Panel F of Appendix Table A22 assigns a false 2014 policy date within 2012–2015 and gives statistically insignificant estimates for both outcomes. Under the city-level wild bootstrap of Appendix Section C, profit per ton remains significant at the 5% level and main-business gross margin at the 10% level.

[49] The 2017 ban on induction-furnace mills (commonly called *ditiaogang*) removed roughly 140 million tons of unlicensed capacity. Because these mills were major scrap buyers, the ban weakened demand for scrap and put downward pressure on scrap prices. For the 140 million ton capacity figure and the associated surge in scrap exports after the *ditiaogang* ban, see China Daily/Xinhua, https://www.chinadaily.com.cn/a/201802/21/WS5a8d8109a3106e7dcc13d3c5.html. On the capacity reform and the scrap export response, see Chen et al. (2018). The timing checks later in this section (Appendix Table A22) examine the extent to which these concurrent shocks account for the estimated financial results.

[50] Steel profits hovered near zero during the 2012–2015 industry downturn, so effects expressed relative to the sample mean appear dramatic; the per-standard-deviation magnitude and the comparison with operating revenue per ton are more informative.

[51] Shandong, which contributes to the identifying variation in the production regressions, has a single firm in the financial sample and drops out as a singleton.

Table 4: Good-Air Days Target Intensity, Financial Outcomes, and Labor Costs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome group		Profitability		Per-ton accounting		Labor costs	
Dependent variable	Pre-tax profit/ton	Main-business gross margin	Aggregate net profit	Operating revenue/ton	Operating cost/ton	Wage bill/ton	Annual wage/worker
Units	2015 CNY	Percentage points	10k 2015 CNY	2015 CNY	2015 CNY	2015 CNY	2015 CNY
Target intensity × Post	243.449***	6.710***	172,420*	-778.705	-902.664	12.575	11,028*
	(35.252)	(1.414)	(84,573)	(700.334)	(625.735)	(22.041)	(6,487)
Observations	343	343	298	299	299	341	211
R^2	0.797	0.730	0.673	0.932	0.933	0.830	0.813
City controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	130.2	9.247	80,750	5,664	5,566	159.7	52,468

Notes: Each column reports a continuous difference-in-differences estimate from Equation (2) in the matched financial panel. Column (1) is CISA's reported pre-tax profit per ton of crude steel, and column (2) is main-business revenue minus main-business cost over main-business revenue. Columns (4)–(5) use the 299 firm-years in which operating revenue, operating cost, and pre-tax profit per ton are all observed, and both per-ton measures are winsorized at the 1st and 99th percentiles. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To investigate the sources of higher profits, columns (4)–(5) of Table 4 examine operating revenue and operating cost per ton of crude steel, rather than their levels, which largely reflect firm size. A one-standard-deviation increase in target intensity is associated with declines of about 272 CNY in operating cost per ton and 234 CNY in operating revenue per ton, neither statistically significant.[52] The wage bill per ton of crude steel does not change significantly in column (6), while annual wages per worker rise in column (7), although only at the 10% significance level.[53]

An illustrative input-price calibration in Appendix Section D suggests that greater scrap use could reduce costs, as scrap is cheaper than hot metal during this period. For scale, a back-of-the-envelope calculation in the same appendix puts additional environmental investment at roughly 18 CNY per ton of crude steel, of the same order as the estimated scrap savings and about one-quarter of the increase in pre-tax profit per ton. Profit gains are largest in 2017 and 2018, when scrap is cheapest relative to hot metal following the induction-furnace ban. This pattern is consistent with the input-substitution mechanism, but these years also coincide with a recovery in steel margins, which may have benefited firms in higher- and lower-intensity cities unequally. For the Porter-hypothesis literature, our findings show that greater target intensity is associated with input substitution and higher pre-tax profit per ton during a period when scrap-market conditions make substitution more profitable.

8 Conclusion

Chinese steel firms facing greater air-quality pressure adjust their production processes and increase investment in pollution control. The production adjustment involves greater use of scrap relative to pig iron in existing converters, raising the implied scrap share by about two percentage points. The investment response is concentrated in cities where Good-Air Days targets overlap with winter controls. Firms facing greater pressure do not become less profitable while adjusting. Reported SO_2 emissions, however, do not capture the production adjustment.

The magnitudes are specific to this setting, but the measurement problem is more general. When firms comply along multiple margins, emissions and financial data may miss important changes in how firms produce. Evaluations based on these outcomes alone can overlook the mechanisms of compliance. Which margin dominates depends on input markets, production technology, and firms' operational capabilities.

The two margins also differ in their environmental effects. End-of-pipe equipment treats specific pollutants after they are generated, and its effectiveness depends on continued operation and maintenance. In contrast, input substitution reduces pollution generated by the displaced production stage, including pollutants that end-of-pipe equipment may not capture. This benefit does

[52] Appendix Section D compares the two on the 299 firm-years with complete accounting data.

[53] For completeness, Appendix Table A23 reports estimates for construction in progress and net fixed assets.

not depend on the operation of treatment equipment. However, the scope for scrap substitution is constrained by the converter's heat balance and the availability of scrap, making it a complement to rather than a replacement for end-of-pipe abatement. For regulators, the relevant comparison is the cost of each margin per unit of environmental damage avoided, which depends on production technology, input prices, and the pollutants affected.

This production margin is not unique to steel. Similar adjustments are possible in industries with sequential production stages of different pollution intensities, where an input at a later stage can substitute for output from an earlier stage, including cement, aluminum, pulp and paper, and basic chemicals. Whether firms in these industries use this margin, and whether it improves their financial performance, remain open empirical questions.

References

Albrizio, S., T. Kozluk, and V. Zipperer (2017). Environmental policies and productivity growth: Evidence across industries and firms. *Journal of Environmental Economics and Management 81*, 209–226.

Ambec, S., M. A. Cohen, S. Elgie, and P. Lanoie (2013). The Porter hypothesis at 20: Can environmental regulation enhance innovation and competitiveness? *Review of Environmental Economics and Policy 7*(1), 2–22.

Barbera, A. J. and V. D. McConnell (1990). The impact of environmental regulations on industry productivity: Direct and indirect effects. *Journal of Environmental Economics and Management 18*(1), 50–65.

Berman, E. and L. T. M. Bui (2001). Environmental regulation and productivity: Evidence from oil refineries. *Review of Economics and Statistics 83*(3), 498–510.

Bo, X., M. Jia, X. Xue, L. Tang, Z. Mi, S. Wang, W. Cui, X. Chang, J. Ruan, G. Dong, B. Zhou, and S. J. Davis (2021). Effect of strengthened standards on Chinese ironmaking and steelmaking emissions. *Nature Sustainability 4*, 811–820.

Brandt, L., F. Jiang, Y. Luo, and Y. Su (2022). Ownership and productivity in vertically-integrated firms: Evidence from the Chinese steel industry. *Review of Economics and Statistics 104*(1), 101–115.

Calel, R. and A. Dechezleprêtre (2016). Environmental policy and directed technological change: Evidence from the European Carbon Market. *Review of Economics and Statistics 98*(1), 173–191.

Callaway, B., A. Goodman-Bacon, and P. H. C. Sant'Anna (forthcoming). Difference-in-differences with a continuous treatment. *American Economic Review*.

Cao, G., X. Weng, M. Xu, and L.-A. Zhou (2026). How do bureaucrats respond to hybrid incentive contract? Evidence from China's air pollution controls. *Journal of Public Economics 259*, 105664.

Carlson, C., D. Burtraw, M. Cropper, and K. L. Palmer (2000). Sulfur dioxide control by electric utilities: What are the gains from trade? *Journal of Political Economy 108*(6), 1292–1326.

Chen, L., D. Ding, and R. Mano (2018). China's capacity reduction reform and its impact on producer prices. IMF Working Paper 18/216, International Monetary Fund.

Chen, L., S. Li, and M. Zhou (2026). Environmental regulation, heterogeneous firms, and resource reallocation. UNSW Business School Research Paper. Available at SSRN: https://papers.ssrn.

com/sol3/papers.cfm?abstract_id=6881118.

Chen, P. (2025). Industrialization and pollution: The long-term impact of early-life exposure on human capital formation. *Journal of Public Economics 241*, 105270.

Cohen, M. A. and A. Tubb (2018). The impact of environmental regulation on firm and country competitiveness: A meta-analysis of the Porter hypothesis. *Journal of the Association of Environmental and Resource Economists 5*(2), 371–399.

Collard-Wexler, A. and J. De Loecker (2015). Reallocation and technology: Evidence from the US steel industry. *American Economic Review 105*(1), 131–171.

Colmer, J., R. Martin, M. Muûls, and U. J. Wagner (2025). Does pricing carbon mitigate climate change? firm-level evidence from the European Union Emissions Trading System. *Review of Economic Studies 92*(3), 1625–1660.

Cui, L., M. Liu, X. Yuan, Q. Wang, Q. Ma, P. Wang, J. Hong, and H. Liu (2021). Environmental and economic impact assessment of three sintering flue gas treatment technologies in the iron and steel industry. *Journal of Cleaner Production 311*, 127703.

De Simone, R., S. L. Naaraayanan, and K. Sachdeva (2025). Opening the brown box: Production responses to environmental regulation. Working paper, London Business School.

Dechezleprêtre, A. and M. Sato (2017). The impacts of environmental regulations on competitiveness. *Review of Environmental Economics and Policy 11*(2), 183–206.

Deutsche Energie-Agentur (dena) (2023). Approaches to the low-carbon transition of heavy industries: The role of circular economy measures. Technical report, Deutsche Energie-Agentur.

Dutt, N. and A. A. King (2014). The judgment of garbage: End-of-pipe treatment and waste reduction. *Management Science 60*(7), 1812–1828.

Fan, H., J. S. Graff Zivin, Z. Kou, X. Liu, and H. Wang (2025a). Going green in China: Firms' responses to stricter environmental regulations. *Canadian Journal of Economics 58*(1), 385–410.

Fan, M., S. Ge, H. Li, and J. Zhao (2025b). State ownership and cost-effectiveness of environmental policies: Firm-level evidence. *Economic Inquiry 63*(4), 1252–1278.

Fowlie, M. L. (2009). Incomplete environmental regulation, imperfect competition, and emissions leakage. *American Economic Journal: Economic Policy 1*(2), 72–112.

Ghanem, D. and J. Zhang (2014). 'Effortless Perfection:' Do Chinese cities manipulate air pollution data? *Journal of Environmental Economics and Management 68*(2), 203–225.

Gibson, M. (2019). Regulation-induced pollution substitution. *Review of Economics and Statis-*

tics 101(5), 827–840.

Greenstone, M. (2003). Estimating regulation-induced substitution: The effect of the Clean Air Act on water and ground pollution. *American Economic Review 93*(2), 442–448.

Greenstone, M., G. He, R. Jia, and T. Liu (2022). Can technology solve the principal-agent problem? Evidence from China's war on air pollution. *American Economic Review: Insights 4*(1), 54–70.

Gutiérrez, E. and K. Teshima (2018). Abatement expenditures, technology choice, and environmental performance: Evidence from firm responses to import competition in Mexico. *Journal of Development Economics 133*, 264–274.

Hanna, R. (2010). US environmental regulation and FDI: Evidence from a panel of US-based multinational firms. *American Economic Journal: Applied Economics 2*(3), 158–189.

He, G., S. Wang, and B. Zhang (2020). Watering down environmental regulation in China. *Quarterly Journal of Economics 135*(4), 2135–2185.

He, K., L. Wang, and X. Li (2020). Review of the energy consumption and production structure of China's steel industry: Current situation and future development. *Metals 10*(3), 302.

Jaffe, A. B. and K. Palmer (1997). Environmental regulation and innovation: A panel data study. *Review of Economics and Statistics 79*(4), 610–619.

Jia, W., C. Ma, X. Wang, and R. Xie (2025). Intra-firm pollution leakage and redistribution of pollution exposure: Evidence from coal-regulated plants in China. *Journal of Environmental Economics and Management 133*, 103205.

King, A. and M. Lenox (2002). Exploring the locus of profitable pollution reduction. *Management Science 48*(2), 289–299.

Kong, D. and C. Liu (2024). Centralization and regulatory enforcement: Evidence from personnel authority reform in China. *Journal of Public Economics 229*, 105030.

Lanoie, P., J. Laurent-Lucchetti, N. Johnstone, and S. Ambec (2011). Environmental policy, innovation and performance: New insights on the Porter hypothesis. *Journal of Economics & Management Strategy 20*(3), 803–842.

Levinson, A. (2015). A direct estimate of the technique effect: Changes in the pollution intensity of US manufacturing, 1990–2008. *Journal of the Association of Environmental and Resource Economists 2*(1), 43–56.

Levinson, A. and M. S. Taylor (2008). Unmasking the pollution haven effect. *International Economic Review 49*(1), 223–254.

Li, J., S. Li, and H. Zhang (2026). Output quality, productivity, and demand: Evidence from the Chinese steel industry. *The RAND Journal of Economics 57*(3), 784–807.

Liu, H. (2025). The number of good air quality days in 367 Chinese cities (2014–2024). [DS/OL]. DOI: 10.57760/sciencedb.20703; CSTR: 31253.11.sciencedb.20703; accessed 2026-08-07.

Liu, M., R. Shadbegian, and B. Zhang (2022). Environmental regulation, compliance strategies, and productivity: Evidence from China. *Land Economics 98*(1), 41–61.

Liu, Z., H. Ma, and F. Zhang (2027). Window-dressing in environmental regulation: Short-term incentives and temporary abatement. *Journal of Environmental Economics and Management 141*, 103415.

Lu, R. (2017). Induction furnace closures: Limited upside for hot metal production. CRU Group, Steelmaking Raw Materials.

Lu, Y. and J. Pless (2026). Greening to grow: Evidence from environmental regulation and industrial firm productivity in China. *Journal of Public Economics 256*, 105596.

Memon, S. F., S. C. Kumbhakar, and Y. Su (2026). Does pollution prevention enhance firm efficiency? Insights from US manufacturing firms. *International Journal of Industrial Organization 107*, 103305.

Ministry of Environmental Protection (2016). Technical specifications of flue gas limestone/lime-gypsum desulfurization project for iron and steel industry sintering machine. Technical Report HJ 2052-2016, Ministry of Environmental Protection, People's Republic of China.

Murray-Leclair, E. (2026). Asymmetric environmental regulation, interfuel substitution and carbon leakage. *Journal of Environmental Economics and Management 136*, 103263.

Najjar, N. and J. Cherniwchan (2021). Environmental regulations and the cleanup of manufacturing: Plant-level evidence. *Review of Economics and Statistics 103*(3), 476–491.

Porter, M. E. and C. van der Linde (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspectives 9*(4), 97–118.

Qi, Y., J. Zhang, and J. Chen (2023). Tax incentives, environmental regulation and firms' emission reduction strategies: Evidence from China. *Journal of Environmental Economics and Management 117*, 102750.

Rexhäuser, S. and C. Rammer (2014). Environmental innovations and firm profitability: Unmasking the Porter hypothesis. *Environmental and Resource Economics 57*(1), 145–167.

Reynaert, M. (2021). Abatement strategies and the cost of environmental regulation: Emission standards on the European car market. *Review of Economic Studies 88*(1), 454–488.

Rijal, B. and N. Khanna (2020). High priority violations and intra-firm pollution substitution. *Journal of Environmental Economics and Management 103*, 102359.

Rodrigue, J., D. Sheng, and Y. Tan (2022). The curious case of the missing Chinese emissions. *Journal of the Association of Environmental and Resource Economists 9*(4), 755–805.

Rodrigue, J., D. Sheng, and Y. Tan (2024). Exporting, abatement, and firm-level emissions: Evidence from China's accession to the WTO. *Review of Economics and Statistics 106*(4), 1064–1082.

Ryan, S. P. (2012). The costs of environmental regulation in a concentrated industry. *Econometrica 80*(3), 1019–1061.

Schäfer, M., U. Faltings, and B. Glaser (2025). Machine learning approach for predicting tramp elements in the basic oxygen furnace based on the compiled steel scrap mix. *Scientific Reports 15*, 2430.

Shangguan, F., Z. Duan, Z. Cui, W. Ma, X. Li, B. Wang, B. Yang, and Z. Liu (2024). Discussion on several issues of carbon peak and carbon neutrality in China's steel industry under new situation. *Iron and Steel 59*(9), 22–31. In Chinese.

Shapiro, J. S. and R. Walker (2018). Why is pollution from US manufacturing declining? the roles of environmental regulation, productivity, and trade. *American Economic Review 108*(12), 3814–3854.

Shi, X. and Z. Xu (2018). Environmental regulation and firm exports: Evidence from the eleventh Five-Year Plan in China. *Journal of Environmental Economics and Management 89*, 187–200.

Tian, R., H. Wang, D. Zhang, X. Zhang, and T. Sterner (2026). Heterogeneous responses to carbon pricing: firm-level evidence from Beijing emissions trading scheme. *Journal of Environmental Economics and Management 136*, 103266.

Voraberger, B., G. Wimmer, U. Dieguez Salgado, E. Wimmer, K. Pastucha, and A. Fleischanderl (2022). Green LD (BOF) steelmaking—reduced CO_2 emissions via increased scrap rate. *Metals 12*(3), 466.

Wu, W., Q. Tang, W. Xue, X. Shi, D. Zhao, Z. Liu, X. Liu, C. Jiang, G. Yan, and J. Wang (2024). Quantifying China's iron and steel industry's CO_2 emissions and environmental health burdens: A pathway to sustainable transformation. *Environmental Science and Ecotechnology 20*, 100367.

Zhang, R., H. Li, and N. Khanna (2025). Monitoring and enforcement and environmental compliance: Power plant emissions during the 2018–19 federal government shutdown. *Journal of the Association of Environmental and Resource Economists 12*(5), 1355–1388.

Appendices

Appendix A: Tables

Table A1: Concurrent Clean-Air and Steel-Sector Policies

Policy	Timing	Scope	Treatment in this paper
Air Pollution Prevention and Control Action Plan	Sept. 2013; targets for 2017	National, with regional targets	Pre-period; regional components absorbed by province-by-year fixed effects
Revised Environmental Protection Law	Effective Jan. 2015	National	Absorbed by province-by-year fixed effects
Steel capacity reduction (supply-side reform)	From Feb. 2016	National target, provincial quotas	National and provincial totals absorbed by province-by-year fixed effects; within-province allocation not absorbed; crude-steel output unchanged (Table 2)
Central environmental protection inspections	First round 2016–2017	Province by province	Absorbed by province-by-year fixed effects
Induction-furnace ban	Completed mid-2017	National	Response dated to 2017, with 2016 estimates near zero; pig-iron estimate robust to dropping 2017 (Appendix Section C)
"2+26" autumn–winter controls	From winter 2017–2018	28 cities in and around Beijing–Tianjin–Hebei	Controlled for and excluded (Section 5.3)
Environmental Protection Tax	Effective Jan. 2018	National, provincial rates	Absorbed by province-by-year fixed effects
Three-Year Action Plan for Winning the Blue Sky War	2018–2020	National, with key regions	Key-region overlap with "2+26" examined in Section 5.3
Ultra-low-emission retrofits for steel	From Apr. 2019	National	Final sample year; robust to dropping 2019 (Section 5.1)

Table A2: Target Intensity and Realized Good-Air Days

Dependent variable	(1) Realized/baseline	(2) Realized/baseline	(3) Realized change
Units	Ratio	Ratio	Days
Target intensity (target/baseline)	0.392***		46.00***
	(0.075)		(11.89)
Required improvement (binding cities)		0.394***	
		(0.111)	
Distance above target (attaining cities)		-0.409	
		(0.300)	
Already attaining (=1)		0.004	
		(0.041)	
Province FE	Yes	Yes	Yes
Cities	54	54	54

Notes: City-level cross-section of the 54 cities in the main firm sample; Suzhou enters with its prefecture-level baseline and target. Realized/baseline is the 2016–2019 average number of Good-Air Days over the 2014–2015 average, and the realized change is their difference. In column (2), the required improvement is the target minus the baseline, divided by the baseline, for cities whose target exceeds their baseline (zero otherwise); the distance above target is the baseline minus the target, divided by the baseline, for cities that already met their target (zero otherwise); and already attaining is an indicator for the latter group. Because the ratios in columns (1)–(2) share the baseline denominator, part of their association with target intensity is mechanical. Appendix Figure B3 reports column (3) year by year. Standard errors clustered at the province level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: Summary Statistics

Variable	(1) Mean	(2) SD	(3) Min	(4) Max	(5) N
Panel A. Treatment					
Baseline Good-Air Days (2014–15 avg.)	233.2	67.0	110.0	359.0	546
2020 target Good-Air Days	270.5	34.4	205.0	338.0	546
Target intensity (target/baseline)	1.237	0.301	0.767	2.091	546
Panel B. Production outcomes (regression sample)					
Pig iron / crude steel	0.944	0.122	0.380	1.246	389
Sintering / crude steel	1.446	0.343	0.432	2.585	364
Crude steel production (10,000 tons)	579.5	512.2	24.6	2385.0	436
Panel C. Abatement investment and mechanism variables					
Total environmental investment (10,000 CNY, 2015 prices)	24,039	40,774	27	324,681	338
Air-pollution investment (10,000 CNY, 2015 prices)	19,511	36,267	27	255,169	320
Air investment share	0.788	0.252	0.009	1.000	320
Water investment share	0.207	0.217	0.001	1.000	156
Purchased scrap / crude steel (scrap subsample)	0.070	0.059	0.000	0.292	59
SO_2 per 10,000 tons of crude steel (tons)	7.843	6.377	0.408	43.758	416
Panel D. Financial outcomes (matched financial panel)					
Pre-tax profit / crude-steel ton (2015 CNY)	130.2	248.5	-742.3	1010.5	343
Main-business gross margin (percent)	9.25	6.36	-24.18	32.87	343
Aggregate net profit after tax (10,000 CNY, 2015 prices)	80,750	227,019	-1,176,522	1,884,078	298

Notes: The main sample covers 2012–2019 and includes firms whose principal product is crude steel and that have at least seven firm-year observations, excluding six specialty-steel producers without basic-oxygen-furnace equipment (546 firm-years). Each row uses that variable's estimation sample. Production ratios and crude-steel output are winsorized at the 1st and 99th percentiles. Purchased scrap comes from the 59-observation scrap-reporting subsample (Section 4.1), and Panel D from the matched financial panel, which consists mainly of listed firms.

Table A4: Pre-Treatment Balance Check

Panel A. Production outcomes

	(1)	(2)	(3)
Dependent variable	Pig iron/ crude steel	Sintering/ crude steel	Crude-steel output
Units	Tons/ton	Tons/ton	10k tons
Target intensity	0.015	-0.153	-121.245
	(0.036)	(0.141)	(158.664)
Observations	54	52	58
R^2	0.336	0.279	0.339
Province FE	Yes	Yes	Yes
Dep. var. mean	0.963	1.481	538.2

Panel B. Emissions, investment, and ownership

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Total SO_2	SO_2/ crude steel	Environmental investment	Air investment share	Private ownership
Units	Log	Log	10k 2015 CNY	Share	Indicator
Target intensity	-0.250	0.088	-13,172	-0.090	0.106
	(0.549)	(0.372)	(10,604)	(0.072)	(0.339)
Observations	57	57	51	51	58
R^2	0.235	0.276	0.430	0.288	0.143
Province FE	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	7.968	2.050	15,198	0.804	0.586

Notes: Each coefficient is from a separate cross-sectional regression of the firm's mean 2012–2015 outcome on target intensity, one observation per firm. Observations fall below the 70 sample firms because some firms do not report the outcome and twelve firms are the only sample firm in their province, so province fixed effects absorb them. Heteroskedasticity-robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: Sintering per Ton of Pig Iron

	(1)	(2)
Dependent variable	Sintering/pig iron	
Units	Tons/ton	
Specification	DiD	Event study
Target intensity × Post	-0.047	
	(0.082)	
Target intensity × 2012		0.042
		(0.051)
Target intensity × 2013		0.048
		(0.074)
Target intensity × 2014		0.023
		(0.093)
Target intensity × 2016		0.035
		(0.070)
Target intensity × 2017		-0.055
		(0.109)
Target intensity × 2018		0.037
		(0.083)
Target intensity × 2019		-0.091
		(0.154)
Observations	364	364
R^2	0.719	0.721
City controls	Yes	Yes
Firm FE	Yes	Yes
Province-by-year FE	Yes	Yes
Dep. var. mean	1.523	1.523

Notes: Column (1) reports the estimate from Equation (2), and column (2) the event-study coefficients from Equation (1), with 2015 as the omitted year. Both use the firm-years of column (2) of Table 2, where sintering output is reported. The ratio is winsorized at the 1st and 99th percentiles. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6: Purchased Scrap per Ton of Crude Steel and of Pig Iron

Dependent variable	(1) Purchased scrap/ crude steel	(2) Purchased scrap/ pig iron
Units	Tons/ton	Tons/ton
Target intensity × Post	0.134*	0.140
	(0.064)	(0.088)
Firm-level scrap price	0.007	0.006
	(0.028)	(0.037)
Observations	59	59
R^2	0.919	0.903
City controls	Yes	Yes
Firm FE	Yes	Yes
Province-by-year FE	Yes	Yes
Dep. var. mean	0.0701	0.0770

Notes: Each column reports a continuous difference-in-differences estimate from Equation (2) in the scrap-reporting subsample, 59 firm-years from the unrestricted environmental panel that are not subject to the seven-observation rule. Scrap purchases in levels give a positive but imprecise estimate (32.6 in 10,000 tons). The firm-level scrap price is in 1,000 CNY per ton at 2015 prices. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7: Robustness Checks: Timing and Sample Rules

Dependent variable	(1) Pig iron/ crude steel	(2) Sintering/ crude steel	(3) Env. investment	(4) Air investment
Units	Tons/ton	Tons/ton	10k 2015 CNY	10k 2015 CNY
Panel A. Placebo year 2014, 2012–2015 only				
Treatment	-0.023	-0.042	6,524	6,102
	(0.032)	(0.065)	(10,932)	(10,128)
Observations	173	162	163	152
R^2	0.867	0.835	0.622	0.563
Dep. var. mean	0.973	1.501	16,219	12,847
Panel B. Drop 2019				
Treatment	-0.068**	-0.138*	39,667***	33,818***
	(0.028)	(0.079)	(13,566)	(10,117)
Observations	333	313	293	276
R^2	0.783	0.801	0.593	0.592
Dep. var. mean	0.954	1.462	20,182	16,416
Panel C. Minimum observations ≥ 6				
Treatment	-0.048	-0.180*	32,338**	30,584**
	(0.033)	(0.095)	(12,801)	(12,599)
Observations	469	443	416	398
R^2	0.756	0.762	0.575	0.573
Dep. var. mean	0.949	1.444	22,392	18,020
City controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes

Notes: Each panel changes one element of Equation (2), named in the panel title. In Panel A, Post equals one from 2014 and the sample is 2012–2015. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8: Attrition, Sample Selection, and Outcome Reporting

	(1) Coefficient on target intensity	(2) SE	(3) p	(4) Mean of dep. var.
Panel A. Firm level: target intensity				
Exit before 2018 (=1)	0.027	(0.205)	0.896	0.316
Included in main sample, $\geq$7 obs (=1)	-0.018	(0.240)	0.942	0.515
Panel B. Firm-year: target intensity $\times$ *Post*				
Pig iron / crude steel reported (=1)	-0.010	(0.015)	0.500	0.915
Sintering / crude steel reported (=1)	-0.014	(0.023)	0.536	0.862
Environmental investment reported (=1)	-0.099	(0.162)	0.544	0.803
Air-pollution investment reported (=1)	-0.054	(0.143)	0.708	0.775

Notes: Each row is a separate regression. Panel A is a firm-level cross-section of the unrestricted crude-steel panel, restricted to firms observed before 2015, with province fixed effects; exit before 2018 equals one if the firm's last observation predates 2018, and inclusion equals one if the firm meets the seven-observation rule. Panel B uses the firm-year estimation sample and regresses an indicator that the outcome is reported on target intensity $\times$ Post with the specification of Equation (2); column (4) is the share of firm-years in which the outcome is reported. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9: Robustness Checks: Alternative Treatment Measures

Dependent variable	(1) Pig iron/ crude steel	(2) Sintering/ crude steel	(3) Env. investment	(4) Air investment
Units	Tons/ton	Tons/ton	10k 2015 CNY	10k 2015 CNY
Panel A. Realized-improvement treatment				
Treatment	-0.180**	-0.692***	64,625*	58,472*
	(0.085)	(0.242)	(34,733)	(33,891)
Observations	389	364	338	320
R^2	0.801	0.807	0.579	0.570
Dep. var. mean	0.944	1.446	24,039	19,511
Panel B. Level treatment (target minus baseline, per 10 days)				
Treatment	-0.006**	-0.010	2,271**	2,064**
	(0.002)	(0.007)	(964.749)	(916.016)
Observations	389	364	338	320
R^2	0.802	0.799	0.580	0.571
Dep. var. mean	0.944	1.446	24,039	19,511
City controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes

Notes: Each panel replaces target intensity in Equation (2) with the measure named in the panel title, interacted with Post. Realized improvement is the ratio of a city's average Good-Air Days over 2016–2019 to its 2014–2015 baseline. The level treatment is the end-of-plan target minus the baseline, in units of 10 Good-Air Days. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A10: Provincial and City-Level Good-Air Days Targets

Province	City	Baseline days	Kong–Liu target (days)	City-level target (%)	City-level target (days)	Firm-years	Source
Beijing	Beijing	174.0	205	56.0	205	16	d
Chongqing	Chongqing	269.5	303	83.0	303	8	f
Hebei	Chengde	250.0	230	78.0	285	8	d
Hebei	Handan	126.5	230	52.1	190	24	d
Hebei	Shijiazhuang	140.0	230	63.0	230	24	e
Hebei	Xingtai	110.0	230	57.4	210	16	e
Hebei	Zhangjiakou	300.0	230	90.0	329	7	e
Henan	Anyang	152.5	237	59.2	216	15	d
Henan	Jiyuan†	178.0	237	80.0	292	8	d
Henan	Pingdingshan	152.0	237	60.0	219	8	d
Hubei	Ezhou	205.0	266	73.0	266	8	d
Hubei	Huangshi	244.0	296	81.0	296	8	h
Jiangsu	Changzhou	237.5	263	73.3	268	8	a
Jiangsu	Huai'an	227.0	263	73.3	268	8	a
Jiangsu	Lianyungang	251.0	263	76.2	278	7	a
Jiangsu	Nanjing	211.0	263	71.0	259	8	a
Jiangsu	Suzhou (Changshu)	282.0	263	72.9	266	8	a
Jiangsu	Suzhou (Zhangjiagang)	237.0	263	72.9	266	16	a
Jiangsu	Wuxi	228.0	263	71.1	260	16	a
Jiangsu	Xuzhou	230.5	263	70.2	256	7	a
Jiangsu	Yancheng	264.0	263	77.1	281	7	a
Jilin	Changchun	235.5	292	80.0	292	8	g
Liaoning	Anshan	223.5	292	70.2	256	15	b
Liaoning	Benxi	280.0	292	80.0	292	8	b
Liaoning	Chaoyang (Lingyuan)	298.0	292	77.0	281	8	b
Liaoning	Dalian	274.0	292	80.2	293	8	b
Liaoning	Fushun	250.5	292	78.0	285	8	b
Liaoning	Yingkou	269.0	292	74.0	270	8	b
Shandong	Jinan	110.5	226	62.0	226	8	c
Shandong	Rizhao	235.5	226	78.5	287	8	c
Shanghai	Shanghai	265.0	274	75.1	274	8	d
Shanxi	Changzhi	242.5	275	75.4	275	8	d
Tianjin	Tianjin	194.5	256	70.0	256	23	d

Notes: Sample target locations whose 2020 Good-Air Days target an official document gives for the city itself, either as a city-specific value or as a value that confirms the Kong–Liu target. These locations form the documented-target subsample of Section 5.2. Baseline days are the 2014–2015 average. The Kong–Liu target is the value in Kong and Liu (2024), used in the main specification. City-level targets in days equal the percentage times 365, rounded, except for Jiyuan, whose plan states 292 days. Changshu and Zhangjiagang are county-level cities in Suzhou with their own baselines; Lingyuan is a county-level city in Chaoyang. Sources: (a) Jiangsu Provincial Government, *13th Five-Year Plan for Ecological and Environmental Protection*, Box 2; (b) Liaoning Provincial Government, Liaozhengfa [2018] No. 31, Annex 1; (c) Shandong Provincial Government, *Action Plan for Winning the Blue Sky Defense War* (2018), annex; (d) the city's 13th Five-Year Plan for environmental protection; (e) the city's 13th Five-Year Plan outline; (f) Chongqing Municipal Government, *14th Five-Year Plan for Ecological and Environmental Protection*, review of the 13th Five-Year Plan indicators; (g) Jilin Provincial Government, Jizhengbanfa [2017] No. 7; (h) Hubei Provincial Government, Ezhengfa [2016] No. 48, annex. Shijiazhuang's outline adopts the provincial target without stating a number; the Tianjin plan is taken from a secondary repost. † Not in the regressions because city controls are missing.

Table A11: Robustness to City-Level Good-Air Days Targets

Dependent variable	(1) Pig iron/ crude steel	(2) Sintering/ crude steel	(3) Env. investment	(4) Air investment	(5) Pre-tax profit/ton	(6) Main-business gross margin
Units	Tons/ton	Tons/ton	10k 2015 CNY	10k 2015 CNY	2015 CNY	Percentage points
Panel A. City-level targets, all firms						
Treatment	-0.127**	-0.284*	47,444**	48,166**	340.193***	9.465***
	(0.051)	(0.155)	(20,509)	(20,032)	(79.812)	(2.957)
Observations	389	364	338	320	343	343
Panel B. City-level targets, cities with a documented target						
Treatment	-0.119**	-0.277	54,835**	54,950**	309.120***	8.251***
	(0.050)	(0.172)	(22,157)	(20,297)	(74.075)	(2.058)
Observations	281	256	236	225	246	246
City controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Panels A and B replace the Kong–Liu target with the city-level target in Appendix Table A10, keeping the Kong–Liu target where no city-level document exists. Panel B keeps only firms in cities whose target is documented at the city level, either as a city-specific target or as a city document that confirms the Kong–Liu value. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A12: Treating Already-Compliant Cities as Untreated: Target Intensity Floored at One

Dependent variable	(1) Pig iron/ crude steel	(2) Sintering/ crude steel	(3) Env. investment	(4) Air investment
Units	Tons/ton	Tons/ton	10k 2015 CNY	10k 2015 CNY
Panel A. Production ratios and abatement investment				
Target intensity × Post	-0.076**	-0.166*	38,997***	36,089***
	(0.031)	(0.099)	(13,677)	(13,197)
Target intensity floored at one × Post	-0.081**	-0.186*	45,211***	42,265***
	(0.035)	(0.110)	(15,060)	(14,330)
Effect of 1 SD, target intensity	-0.023	-0.050	11,738	10,863
Effect of 1 SD, floored measure	-0.023	-0.053	12,885	12,046
Observations	389	364	338	320
Dep. var. mean	0.944	1.446	24,039	19,511
Dependent variable	(5) SO_2 per crude steel	(6) Purchased scrap/ crude steel	(7) Pre-tax profit/ton	(8) Main-business gross margin
Units	Log	Tons/ton	2015 CNY	Percentage points
Panel B. Emissions, scrap, and profitability				
Target intensity × Post	-0.655**	0.134*	243.4***	6.710***
	(0.285)	(0.064)	(35.3)	(1.414)
Target intensity floored at one × Post	-0.730**	0.105*	277.2***	7.272***
	(0.301)	(0.059)	(46.2)	(1.882)
Effect of 1 SD, target intensity	-0.197	0.020	73.3	2.020
Effect of 1 SD, floored measure	-0.208	0.014	79.0	2.073
Observations	416	59	343	343
Dep. var. mean	1.746	0.070	130.2	9.25
City controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes

Notes: Each column reports two regressions on the same sample. The first row repeats the baseline estimate; the second replaces target intensity with target intensity floored at one, which sets it to one for the 14 target locations whose baseline already met their target. The floor affects 15 firms and 92 of the 389 firm-years in column (1). Without the floor the measure would equal target intensity and reproduce the baseline estimates exactly. One-standard-deviation effects use the main-sample standard deviations (0.301 and 0.285), except in column (6), which uses the scrap-subsample standard deviation as in Appendix Table A6 and also controls for the firm's scrap price. Columns (7)–(8) use the matched financial panel. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A13: Robustness to City-Specific "2+26" Winter Controls

Dependent variable	(1) Pig iron/ crude steel	(2) Sintering/ crude steel	(3) Env. investment	(4) Air investment
Units	Tons/ton	Tons/ton	10k 2015 CNY	10k 2015 CNY
Panel A. Control for "2+26" exposure				
Treatment	-0.128**	-0.393**	15,562	15,873
	(0.051)	(0.160)	(19,674)	(17,246)
Observations	389	364	338	320
R^2	0.802	0.803	0.587	0.579
Dep. var. mean	0.944	1.446	24,039	19,511
Panel B. Drop "2+26" cities				
Treatment	-0.409***	-0.607*	9,070	2,299
	(0.118)	(0.341)	(53,534)	(46,548)
Observations	216	216	188	176
R^2	0.748	0.796	0.523	0.501
Dep. var. mean	0.923	1.396	22,724	18,630
City controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes

Notes: Panel A adds the interaction of Post with an indicator for the 28 cities in the "2+26" winter-control program. Panel B drops those cities. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A14: Robustness to Differential Trends by Baseline Characteristics

Dependent variable Units	(1) Pig iron/ crude steel Tons/ton	(2) Sintering/ crude steel Tons/ton	(3) Env. investment 10k 2015 CNY	(4) Air investment 10k 2015 CNY
Baseline	-0.076**	-0.166*	38,997***	36,089***
	(0.031)	(0.099)	(13,677)	(13,197)
+ Year × large firm	-0.081**	-0.174*	47,178***	42,304***
	(0.038)	(0.099)	(12,958)	(12,136)
+ Year × heavy polluter	-0.071**	-0.159	40,179***	36,601***
	(0.029)	(0.106)	(9,255)	(8,491)
+ Year × private ownership	-0.071**	-0.161	38,338***	35,325**
	(0.032)	(0.098)	(14,011)	(14,147)
+ Year × high-income city	-0.079**	-0.174*	34,783**	32,258**
	(0.030)	(0.100)	(13,809)	(12,289)
+ All four	-0.087**	-0.186	44,804***	39,944***
	(0.035)	(0.118)	(14,328)	(10,968)
+ Year × log pre-policy city steel output	-0.075**	-0.171*	35,696**	33,194**
	(0.034)	(0.093)	(14,577)	(14,809)
Observations	389	364	338	320
City controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes

Notes: Each row adds the named year-by-characteristic fixed effects to Equation (2). Large firms, heavy polluters, and high-income cities are above the sample median of pre-2015 crude-steel output, pre-2015 SO_2 per ton of crude steel, and 2012–2015 city GDP per capita, respectively. Pre-policy city steel output is the sum of sample firms' mean 2012–2015 crude-steel output in the city. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A15: Baseline Electric-Arc-Furnace Equipment: Interaction Estimates

Dependent variable Units	(1) Pig iron/crude steel Tons/ton	(2) Sintering/crude steel Tons/ton
MIIT equipment classification		
Target intensity × Post	-0.061**	-0.112
	(0.024)	(0.124)
Target intensity × Post × Baseline EAF	-0.039	-0.217
	(0.078)	(0.192)
Observations	340	310
Firms (No EAF/EAF)	31/17	28/16
City controls	Yes	Yes
Firm FE	Yes	Yes
Province-by-year FE	Yes	Yes

Notes: The sample is firms whose pooled 2012–2014 MIIT equipment records list both blast-furnace and basic-oxygen-furnace equipment; Baseline EAF indicates an electric arc furnace in those records. The first row is the effect for firms without baseline EAF equipment, and the second is the additional effect for EAF firms. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A16: Leave-One-Province-Out Estimates

	(1)	(2)	(3)	(4)	(5)
	Dependent variable				
Units	Pig iron/ crude steel Tons/ton	Sintering/ crude steel Tons/ton	Env. investment 10k 2015 CNY	Air investment 10k 2015 CNY	Share of identifying variation Percent
Baseline	-0.076**	-0.166*	38,997***	36,089***	100
	(0.031)	(0.099)	(13,677)	(13,197)	
Excluding Hebei	-0.084	-0.236*	61,427***	62,990***	71
	(0.088)	(0.122)	(11,744)	(11,033)	
Excluding Shandong	-0.106***	-0.173	24,942**	19,449**	21
	(0.036)	(0.122)	(12,034)	(7,644)	
Excluding Liaoning	-0.054**	-0.148*	40,718***	37,011***	4
	(0.023)	(0.087)	(13,345)	(13,206)	
Excluding Jiangsu	-0.064*	-0.149	37,504**	35,220**	2
	(0.032)	(0.109)	(14,742)	(14,248)	
Observations (baseline)	389	364	338	320	
City controls	Yes	Yes	Yes	Yes	
Firm FE	Yes	Yes	Yes	Yes	
Province-by-year FE	Yes	Yes	Yes	Yes	

Notes: Each row re-estimates Equation (2) without the named province; the four provinces are those contributing more than 1% of the identifying variation. Column (5) is each province's share of the summed squared residual of target intensity $\times$ Post after partialling out the controls and both sets of fixed effects, in the column (1) sample. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A17: Heterogeneity by Ownership: Private vs. State-Owned

Panel A. Production outcomes

	(1)	(2)
Dependent variable	Pig iron/ crude steel	Sintering/ crude steel
Units	Tons/ton	Tons/ton
Target int. × Post	-0.002	-0.043
	(0.031)	(0.070)
Target int. × Post × private	-0.156***	-0.251*
	(0.052)	(0.139)
Observations	389	364
R^2	0.808	0.802
City controls	Yes	Yes
Firm FE	Yes	Yes
Province-by-year FE	Yes	Yes
Dep. var. mean	0.944	1.446

Panel B. Environmental investment outcomes

	(1)	(2)
Dependent variable	Total env. investment	Air investment
Units	10k 2015 CNY	10k 2015 CNY
Target int. × Post	44,811***	40,685**
	(15,062)	(15,275)
Target int. × Post × private	-13,290	-10,754
	(21,226)	(18,250)
Observations	338	320
R^2	0.584	0.576
City controls	Yes	Yes
Firm FE	Yes	Yes
Province-by-year FE	Yes	Yes
Dep. var. mean	24,039	19,511

Notes: Each column reports a triple-difference estimate. The first row is the effect for state-owned firms, and the second is the additional effect for private firms. The total effects for private firms are 31,521 (standard error 17,515, $p = 0.080$) for total environmental investment and 29,931 (standard error 16,455, $p = 0.077$) for air-pollution investment. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A18: Heterogeneity by Firm Size

Panel A. Production outcomes

	(1)	(2)
Dependent variable	Pig iron/ crude steel	Sintering/ crude steel
Units	Tons/ton	Tons/ton
Target int. × Post	-0.189***	-0.350***
	(0.043)	(0.122)
Target int. × Post × large	0.190***	0.326
	(0.059)	(0.193)
Observations	389	364
R^2	0.814	0.805
City controls	Yes	Yes
Firm FE	Yes	Yes
Province-by-year FE	Yes	Yes
Dep. var. mean	0.944	1.446

Panel B. Environmental investment outcomes

	(1)	(2)
Dependent variable	Total env. investment	Air investment
Units	10k 2015 CNY	10k 2015 CNY
Target int. × Post	40,828*	37,547**
	(20,379)	(17,203)
Target int. × Post × large	8,642	6,088
	(22,660)	(21,925)
Observations	338	320
R^2	0.592	0.581
City controls	Yes	Yes
Firm FE	Yes	Yes
Province-by-year FE	Yes	Yes
Dep. var. mean	24,039	19,511

Notes: Large equals one for firms above the pre-2015 median of crude-steel output. The first row is the effect for smaller firms, and the second is the additional effect for large firms. The total effects for large firms are 49,470 (standard error 12,139, $p < 0.001$) for total environmental investment and 43,634 (standard error 14,218, $p = 0.004$) for air-pollution investment. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A19: Heterogeneity by Initial Pollution Intensity

Panel A. Production outcomes

	(1)	(2)
Dependent variable	Pig iron/ crude steel	Sintering/ crude steel
Units	Tons/ton	Tons/ton
Target int. × Post	-0.042	-0.141
	(0.051)	(0.119)
Target int. × Post × heavy	-0.037	-0.013
	(0.061)	(0.151)
Observations	389	364
R^2	0.806	0.804
City controls	Yes	Yes
Firm FE	Yes	Yes
Province-by-year FE	Yes	Yes
Dep. var. mean	0.944	1.446

Panel B. Environmental investment outcomes

	(1)	(2)
Dependent variable	Total env. investment	Air investment
Units	10k 2015 CNY	10k 2015 CNY
Target int. × Post	56,410***	47,714***
	(11,591)	(15,920)
Target int. × Post × heavy	-26,823**	-18,247
	(11,804)	(16,965)
Observations	338	320
R^2	0.591	0.581
City controls	Yes	Yes
Firm FE	Yes	Yes
Province-by-year FE	Yes	Yes
Dep. var. mean	24,039	19,511

Notes: Heavy equals one for firms above the pre-2015 median of SO_2 per ton of crude steel. The first row is the effect for initially cleaner firms, and the second is the additional effect for heavy polluters. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A20: Heterogeneity by Baseline Scrap Use

Dependent variable	(1) Pig iron/ crude steel	(2) Sintering/ crude steel	(3) Env. investment	(4) Air investment
Units	Tons/ton	Tons/ton	10k 2015 CNY	10k 2015 CNY
Panel A. Above- versus below-median baseline scrap use				
Target intensity × Post	-0.073	-0.135	46,766*	22,815
	(0.054)	(0.153)	(24,606)	(23,414)
Target intensity × Post × less baseline scrap	-0.005	-0.038	-13,301	12,598
	(0.051)	(0.188)	(24,053)	(23,340)
Total effect, firms with less baseline scrap	-0.078***	-0.173	33,464**	35,413**
	(0.029)	(0.105)	(13,727)	(14,113)
Panel B. Total effect by tercile of baseline scrap use				
Most baseline scrap	-0.142**	-0.264	22,217	12,235
	(0.063)	(0.204)	(25,319)	(23,306)
Middle	-0.241**	-0.336	-11,835	-5,240
	(0.090)	(0.462)	(46,695)	(43,438)
Least baseline scrap	-0.063**	-0.162**	37,068**	38,572**
	(0.028)	(0.072)	(14,263)	(14,650)
Observations	379	356	316	301
City controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes
Scrap group × year FE	Yes	Yes	Yes	Yes

Notes: Baseline scrap use is each firm's mean pig-iron-to-crude-steel ratio over 2012–2014, so a higher ratio means less scrap; firms with no 2012–2014 ratio are excluded. Panel A splits firms at the median: the first row is the effect for firms with more baseline scrap, the second is the additional effect for firms with less, and the third is their sum. Panel B reports the total effect in each tercile. The scrap-group-by-year fixed effects use the median group in Panel A and the tercile in Panel B. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A21: Good-Air Days Target Intensity and Log SO_2 Emissions

Dependent variable	(1) SO_2 per ton of crude steel	(2) Total SO_2	(3) Sintering SO_2
Units	Log	Log	Log
Target intensity × Post	-0.655**	-0.716**	-0.766*
	(0.285)	(0.293)	(0.420)
Observations	416	416	354
R^2	0.832	0.916	0.886
City controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes
Dep. var. mean	1.746	7.765	7.548

Notes: Each column reports a continuous difference-in-differences estimate from Equation (2) for the log of the SO_2 measure in the heading. Before taking logs, column (1) is in tons of SO_2 per 10,000 tons of crude steel, which affects only the dependent-variable mean. Fewer firms report SO_2 from sintering separately, so column (3) has a smaller sample. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A22: Financial Robustness: Timing Checks

	(1)	(2)
Dependent variable	Pre-tax profit/ton	Main-business gross margin
Units	2015 CNY	Percentage points
Panel A. Excluding 2017		
Target intensity × Post	209.870***	5.916***
	(37.023)	(1.393)
Observations	297	297
Dep. var. mean	103.8	8.519
Panel B. Separating 2016 from 2017–2019		
Target intensity × 2016	104.428**	4.438**
	(42.747)	(2.133)
Target intensity × 2017–2019	290.246***	7.475***
	(42.532)	(2.302)
Observations	343	343
Dep. var. mean	130.2	9.247
Panel C. Excluding 2015		
Target intensity × Post	226.567***	6.229***
	(32.351)	(1.056)
Observations	302	302
Dep. var. mean	156.9	9.769
Panel D. Excluding 2017 and 2018		
Target intensity × Post	150.305***	4.552***
	(25.159)	(0.697)
Observations	253	253
Dep. var. mean	53.34	7.352
Panel E. Leaving out one province		
Excluding Hebei	684.095***	12.706
	(191.644)	(7.996)
Excluding Liaoning	241.982***	6.969***
	(32.409)	(1.367)
Excluding Jiangsu	236.100***	6.969***
	(34.808)	(1.533)
Panel F. Placebo year 2014, 2012–2015 only		
Target intensity × Post	-5.390	1.741
	(39.567)	(2.247)
Observations	155	155
Dep. var. mean	-0.928	6.180
City controls	Yes	Yes
Firm FE	Yes	Yes
Province-by-year FE	Yes	Yes

Notes: Each panel re-estimates columns (1) and (2) of Table 4 with one change. Panel A excludes 2017, the year of the national induction-furnace ban, and Panel B replaces Post with separate indicators for 2016 and 2017–2019. Panel C excludes 2015, the trough of the steel-price cycle, and Panel D excludes the peak-margin years 2017 and 2018. Panel E drops, one at a time, the three provinces that contribute identifying variation in the financial sample. Panel F assigns a false policy date of 2014 and uses only 2012–2015. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A23: Financial Outcomes: Capital Investment

Dependent variable	(1) Construction in progress	(2) Net fixed assets
Units	10k 2015 CNY	10k 2015 CNY
Target intensity × Post	-268,556	-268,338
	(293,499)	(269,453)
Observations	336	299
R^2	0.928	0.490
City controls	Yes	Yes
Firm FE	Yes	Yes
Province-by-year FE	Yes	Yes
Dep. var. mean	474,338	2,310,000

Notes: Each column reports a continuous difference-in-differences estimate from Equation (2) in the matched financial panel. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix B: Figures

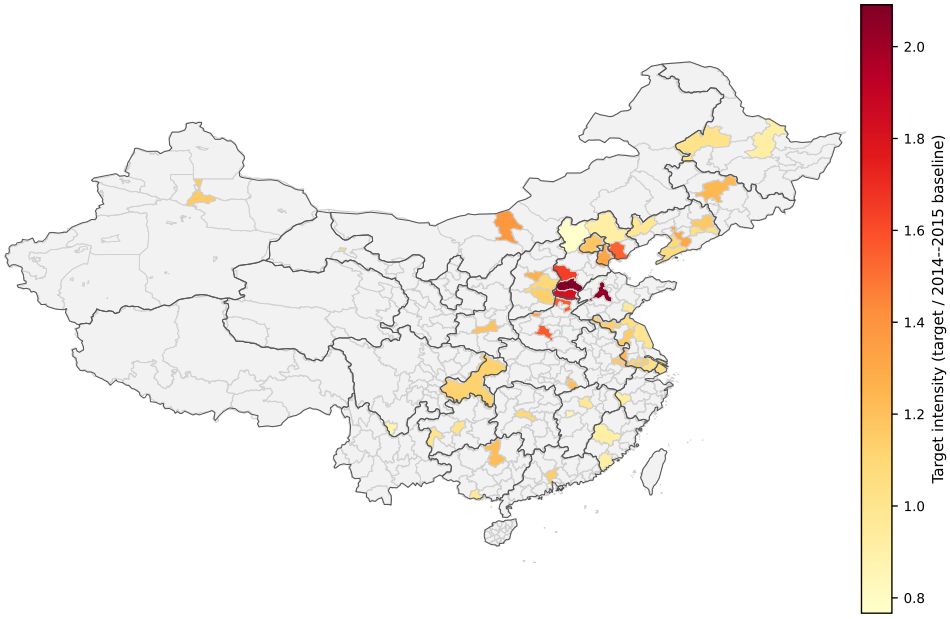


Figure B1: Geographic Distribution of Good-Air Day Target Intensity Across Sample Prefectures. *Notes*: Colored prefectures are represented in the main estimation sample; all other prefectures are shown in gray. Color shows target intensity, defined as the city's Good-Air Days target divided by its 2014–2015 baseline. Darker colors indicate a larger required proportional improvement. Suzhou contains three firms with county-specific baselines; its polygon shows the equally weighted mean across its distinct target assignments. Provincial boundaries, including Taiwan, are overlaid in darker lines. Boundary data are from cn-atlas and geoBoundaries.

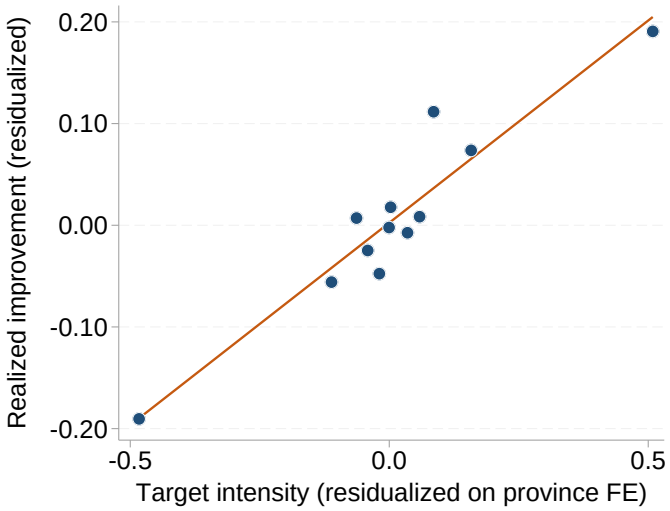


Figure B2: Realized Improvement vs. Target Intensity. *Notes*: Binscatter of realized Good-Air Days improvement against target intensity, residualized on province fixed effects. Dots are means within 15 quantile bins of residualized target intensity; cities in single-city provinces all have a residual of zero and fall in one bin, so fewer than 15 dots appear. The positive slope partly reflects the shared baseline denominator; see Appendix Table A2.

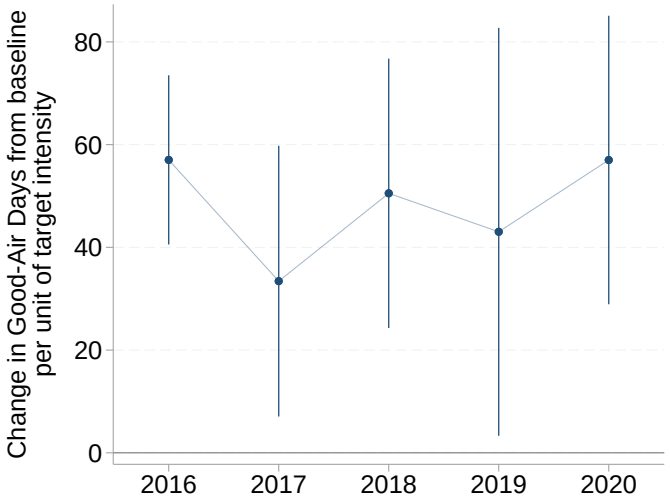


Figure B3: Realized Good-Air Days Improvement by Year. *Notes*: Each point is the coefficient from a separate city-level regression of the change in Good-Air Days between year t and the 2014–2015 baseline on target intensity, with province fixed effects, for the 54 cities in the main sample; vertical lines are 95% confidence intervals with standard errors clustered by province. Annual counts are from Liu (2025). The regressions are suggestive: cities with low baselines have both higher target intensity and more room to improve, and 2020 includes the COVID-19 lockdown period.

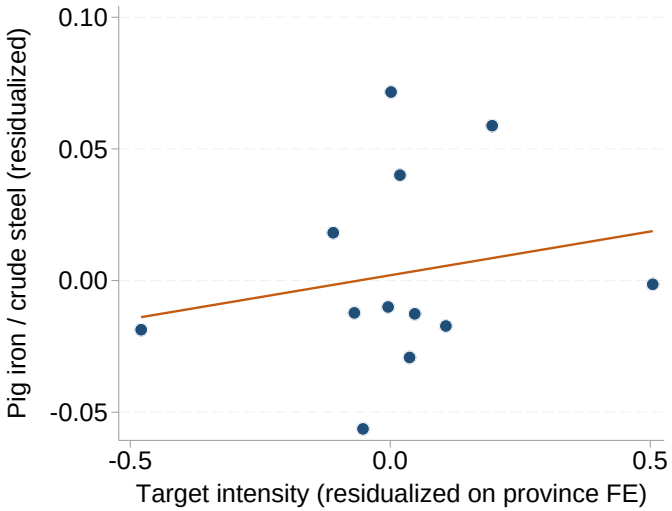


Figure B4: Pre-Policy Production Mix and Good-Air Days Target Intensity. *Notes*: The figure plots each firm's mean pre-policy (2012–2015) pig-iron-to-crude-steel ratio against target intensity, after residualizing both variables on province fixed effects. Dots are means within fifteen quantile bins of residualized target intensity (firms that are alone in their province all have a residual of zero and fall in one bin, so fewer than fifteen dots appear), and the solid line is the fitted linear relationship. The flat slope is the graphical counterpart of the balance estimates in Appendix Table A4.

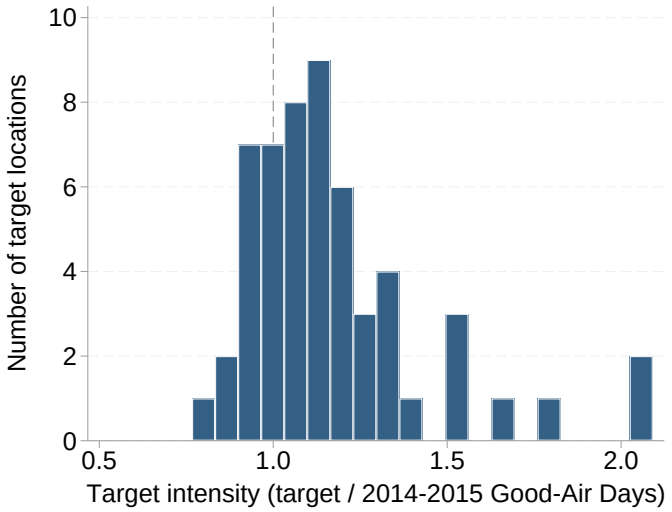


Figure B5: Distribution of Good-Air Days Target Intensity. *Notes*: The figure shows target intensity across steel-producing target locations; the dashed line marks a target equal to the 2014–2015 baseline.

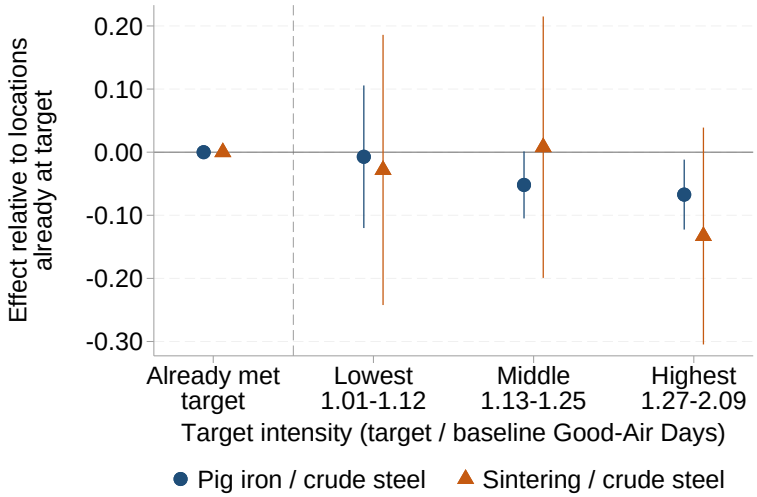
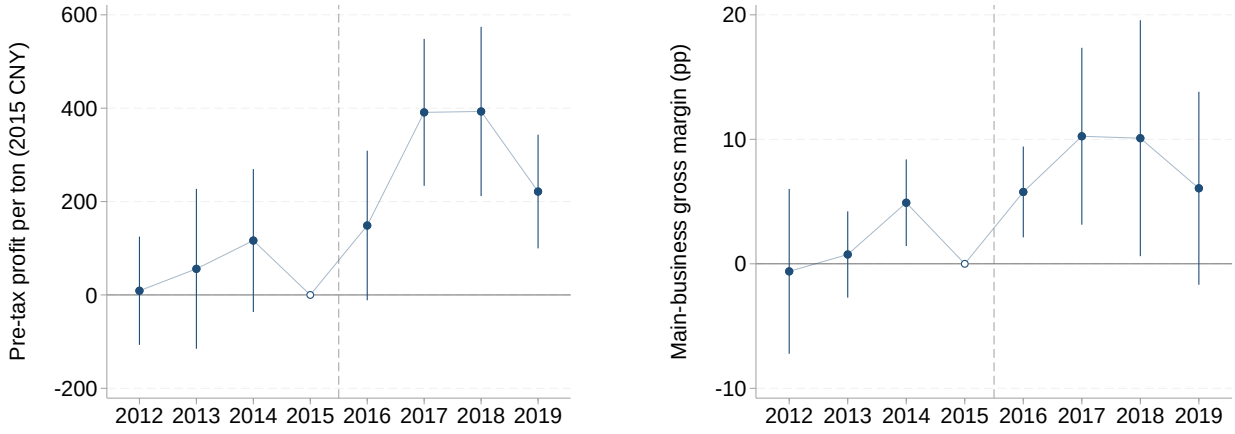


Figure B6: Binned Dose-Response Profile. *Notes*: Coefficients from a specification that replaces the linear dose with group indicators, each interacted with the post-2015 indicator, following the recommendation of Callaway et al. (forthcoming). The omitted group is the target locations whose 2014–2015 baseline already met or exceeded their end-of-plan target ($T_c \leq 1$); the remaining locations are split into terciles of target intensity, spanning 1.01–1.12, 1.13–1.25, and 1.27–2.09. Vertical lines denote city-clustered 95% confidence intervals. Regressions include firm and province-by-year fixed effects and city-level controls. See Section 5.



(a) Pre-tax profit per ton (2015 CNY)

(b) Main-business gross margin (pp)

Figure B7: Event Studies: Financial Outcomes. *Notes*: The y-axis reports the coefficients β_τ estimated from equation (1) in the matched financial sample. The omitted year is 2015, and the vertical dashed line marks the start of the post-treatment period. Vertical lines denote city-clustered 95% confidence intervals. Regressions include firm and province-by-year fixed effects and city-level controls. See Section 7.

References

Callaway, B., A. Goodman-Bacon, and P. H. C. Sant'Anna (forthcoming). Difference-in-differences with a continuous treatment. *American Economic Review*.

Appendix C: Additional Robustness Checks

This appendix gives the details behind the checks that Section 5 summarizes, in the same order, the Poisson estimates noted in Section 4.2, and the checks that Section 5.5 only lists.

Common sample. The four outcomes are reported by different subsets of firm-years, so the baseline estimates come from samples of different sizes. Panel A of Appendix Table C1 restricts all four outcomes to the same 282 firm-years. All four estimates keep their baseline signs and remain statistically significant.

Poisson estimates. Because environmental investment is highly skewed, Panel B of Appendix Table C1 estimates both investment outcomes by Poisson pseudo-maximum likelihood, as noted in Section 4.2. Both estimates remain positive and statistically significant.

Table C1: Common Sample and Poisson Estimates

Dependent variable	(1) Pig iron/ crude steel	(2) Sintering/ crude steel	(3) Env. investment	(4) Air investment
Units	Tons/ton	Tons/ton	10k 2015 CNY	10k 2015 CNY
Panel A. Common sample of the four outcomes				
Target intensity × Post	-0.051*	-0.131**	42,827**	38,803**
	(0.028)	(0.060)	(16,740)	(16,005)
Observations	282	282	282	282
Panel B. Poisson pseudo-maximum likelihood				
Target intensity × Post	–	–	1.617***	1.864***
			(0.297)	(0.339)
Observations			338	320
City controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes

Notes: Panel A re-estimates Equation (2) on the firm-years in which all four outcomes are observed. Panel B estimates the investment outcomes by Poisson pseudo-maximum likelihood, so its coefficients are proportional changes in investment per unit of target intensity. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

City-specific targets. Panel B of Appendix Table A11 keeps only firms in cities whose target is documented at the city level, either as a city-specific target or as a city document that confirms the Kong–Liu value. The estimates are similar to those in Panel A, although the sintering estimate becomes less precise. Columns (5) and (6) of Appendix Table A11 report the profitability outcomes of Section 7, which remain significant at the 1% level in both panels.

Attaining locations and the dose response. The 14 attaining locations are the 13 attaining cities in Section 3 plus the county-level city of Changshu, which already met its target although Suzhou prefecture as a whole had not. Panel B of Appendix Table A12 applies the floored measure to SO_2 intensity, purchased scrap, and the two profitability outcomes. The per-standard-deviation effects are similar to the baseline except for purchased scrap, which is about one-third smaller, and all four estimates keep their baseline signs and statistical significance. For the dose response, the three terciles of target intensity span 1.01–1.12, 1.13–1.25, and 1.27–2.09, and the attaining

locations form the comparison group. In Appendix Figure B6, the lowest-tercile estimates are not statistically distinguishable from zero ($p = 0.90$ for pig iron and $p = 0.79$ for sintering), and the pig-iron estimate grows in magnitude across the three terciles. In the highest tercile, the pig-iron-to-crude-steel estimate is -0.067 and significant at the 5% level.

The "2+26" region. Outside the region, Jiangsu firms account for 40% of the identifying variation, measured as in column (5) of Appendix Table A16. The second row of Appendix Table C2 drops them as well as the 28 cities, which leaves about a third of the baseline observations. The pig-iron-to-crude-steel estimate of -0.268 is larger in magnitude than the baseline but not statistically significant, and the investment estimates turn negative but are imprecise. Within the region, the third row of Appendix Table C2 drops the 5 firms in "2+26" cities in Shandong, Shanxi, and Henan. The total- and air-investment estimates fall to about 65% and 54% of their baseline magnitudes and remain significant at the 5% level, while the pig-iron-to-crude-steel estimate becomes larger in magnitude and the sintering-to-crude-steel estimate becomes imprecise.

Table C2: The "2+26" Region: Excluding Jiangsu and the "2+26" Firms outside Hebei

Dependent variable	(1) Pig iron/ crude steel	(2) Sintering/ crude steel	(3) Env. investment	(4) Air investment
Units	Tons/ton	Tons/ton	10k 2015 CNY	10k 2015 CNY
Baseline	-0.076**	-0.166*	38,997***	36,089***
	(0.031)	(0.099)	(13,677)	(13,197)
Observations	389	364	338	320
Excluding "2+26" cities and Jiangsu	-0.268	-0.360	-51,221	-55,362
	(0.175)	(0.486)	(58,797)	(42,602)
Observations	142	142	124	115
Excluding "2+26" firms outside Hebei	-0.106***	-0.183	25,431**	19,486**
	(0.036)	(0.122)	(12,155)	(7,680)
Observations	342	319	285	268
City controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes

Notes: The first row repeats the baseline estimates in Tables 2 and 3. The second row drops the 28 cities in the "2+26" winter-control program and all Jiangsu firms. The third row drops the 5 firms in "2+26" cities outside Hebei, in Shandong, Shanxi, and Henan. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Supply-side reform and the induction-furnace ban. The 2017 induction-furnace ban removed unlicensed scrap-intensive mills, weakened scrap demand, and raised margins for licensed producers. Cheaper scrap could explain the within-province gradient only if scrap became cheaper where target intensity was higher. With the firm-level purchase price of scrap, in 1,000 CNY per ton at 2015 prices, as the outcome, the baseline specification in the scrap-reporting subsample gives a coefficient of -0.254 ($p = 0.40$, 59 observations). If the estimated production response mainly reflected the ban, it should be concentrated in 2017 and weaken when that year is excluded, and Appendix Table C3 tests both predictions. Panel A of Appendix Table C3 drops 2017, and the pig-iron-to-crude-steel estimate and both investment estimates remain statistically significant despite

the lost year of data, while the sintering-to-crude-steel estimate becomes imprecise. Panel B of Appendix Table C3 separates 2016 from 2017–2019, and the point estimates for both margins are larger in the later period, although the 2016 coefficients are imprecise. Panel C of Appendix Table C3 applies the same split to purchased scrap and gives 0.118 in 2016 and 0.150 in 2017–2019, neither significant at conventional levels. The scrap subsample has observations only for 2012, 2014, 2016, and 2017, so this split compares 2017 with 2016 and cannot date the scrap response relative to the ban. The timing evidence does not support attributing the production or investment responses solely to the ban. As for the supply-side reform, even if capacity reductions affected upstream production, a lower pig-iron-to-crude-steel ratio with unchanged crude-steel output still implies greater scrap use in converters.

Table C3: Supply-Side Reform Robustness: Dropping the Ban Year and Splitting the Post-Period

Dependent variable	(1) Pig iron/ crude steel	(2) Sintering/ crude steel	(3) Env. investment	(4) Air investment
Units	Tons/ton	Tons/ton	10k 2015 CNY	10k 2015 CNY
Panel A. Excluding 2017				
Target intensity × Post	-0.069**	-0.128	37,160**	37,710**
	(0.032)	(0.100)	(17,216)	(17,494)
Observations	335	313	295	277
Dep. var. mean	0.948	1.458	23,808	19,313
Panel B. Separating 2016 from 2017–2019				
Target intensity × 2016	-0.031	-0.034	25,565	16,231
	(0.028)	(0.109)	(16,071)	(16,800)
Target intensity × 2017–2019	-0.091**	-0.212**	41,393***	39,601***
	(0.034)	(0.102)	(14,589)	(14,198)
Observations	389	364	338	320
Dep. var. mean	0.944	1.446	24,039	19,511
Panel C. Scrap-reporting subsample				
Dependent variable	(1) Purchased scrap/ crude steel			
Units	Tons/ton			
Target intensity × 2016	0.118			
	(0.076)			
Target intensity × 2017–2019	0.150			
	(0.088)			
Scrap price	0.004			
	(0.035)			
Observations	59			
Dep. var. mean	0.0701			
City controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes

Notes: Panel A excludes 2017, the year of the national induction-furnace ban. Panel B replaces Post with separate indicators for 2016 and 2017–2019. Panel C applies the split of Panel B to the 59-observation scrap-reporting subsample and controls for the firm's scrap price; that subsample has observations only for 2012, 2014, 2016, and 2017, so its 2017–2019 coefficient comes from 2017 alone. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Differential trends by baseline characteristics. Firms and cities may differ in their capacity to adjust production or reduce pollution, which could generate trends correlated with target intensity. Appendix Table A14 adds year effects interacted with four pre-policy characteristics, one at a time and jointly: above-median firm size, above-median SO_2 intensity, private ownership, and above-median city GDP per capita. The pig-iron-to-crude-steel and investment estimates change little and remain statistically significant in every specification, and the sintering-to-crude-steel estimate is similar in magnitude and remains near the 10% significance threshold, as in the baseline. The last row, used in Section 5.3, interacts year indicators with log pre-policy city steel output, which within provinces is only weakly correlated with target intensity (0.08).

Electric-arc-furnace production. We use furnace-level equipment records from China's Ministry of Industry and Information Technology (MIIT) to distinguish shifts in production route from greater scrap use within the existing blast-furnace/basic-oxygen-furnace (BF–BOF) route. The records come from the compliant-firm lists published under MIIT's Steel Industry Standard Conditions (*Gangtie Hangye Guifan Tiaojian*) program (three batches published in 2012–2014), together with the program's subsequent revocation and equipment-change announcements of 2018–2020. We hand-collect each announcement and compile the type, size, and count of every listed furnace into a single firm-level capacity dataset. Our baseline classification pools the 2012–2014 equipment records and identifies whether each firm is listed with a blast furnace, a basic oxygen furnace, or an electric arc furnace (EAF). We use the 2019 snapshot only to describe changes in EAF status over the study period.

The compiled dataset lists 94 firms with at least one EAF among 304 firms at baseline and 87 such firms among 290 firms in 2019. These totals reflect the composition of each administrative listing; they are not a balanced-panel count of physical openings and closures.

We manually match CISA reporting entities to MIIT firm identifiers, including cases in which a CISA group corresponds to multiple listed entities. The match covers 66 of 70 CISA firms in our baseline estimation: 24 have a baseline EAF and 42 do not. Among matched firms without a baseline EAF, only 1 is listed with an EAF in 2019. Because appearance in a later administrative list does not precisely date physical installation, we use this count only descriptively.

For the heterogeneity analysis, we hold the underlying production route comparable by restricting the sample to the 63 firms with both reported blast-furnace and basic-oxygen-furnace equipment at baseline; 41 have no listed baseline EAF and 22 do. We interact baseline EAF status with target intensity and Post in the baseline specification with firm and province-by-year fixed effects. The regressions use fewer firms than this count, as reported in Appendix Table A15, because some firms lack the outcome or are dropped as singletons under the fixed effects.

If firms responded by shifting production toward existing EAF capacity, both production ratios should fall more among firms with a baseline EAF. For pig iron relative to crude steel, the effect among non-EAF firms is -0.061, while the triple-interaction estimate is -0.039 ($p = 0.667$ under the wild cluster bootstrap). For sintering relative to crude steel, the corresponding estimates are -0.112 and -0.217 ($p = 0.311$). With few EAF owners, these comparisons are imprecise, and neither difference is statistically significant. Combined with how rarely new EAF capacity was listed, they make a shift toward EAF production an unlikely explanation for the production-ratio response.

Influential provinces. Without Hebei, the sintering-to-crude-steel estimate in Appendix Table A16 is significant at the 10% level. Without Shandong, the pig-iron-to-crude-steel estimate is

-0.106, larger in magnitude than the baseline, the sintering-to-crude-steel estimate becomes imprecise, and the investment estimates fall but remain significant at the 5% level. Dropping Liaoning or Jiangsu leaves all four estimates close to their baseline magnitudes.

Alternative inference. The main tables cluster standard errors by city, the level at which targets are assigned. Appendix Table C4 clusters by province, allowing residual correlation across cities exposed to the same provincial enforcement, planning, and steel-market shocks; all four main estimates remain statistically significant. Because conventional cluster-robust inference can overreject when clusters are few or unequal in size (Cameron and Miller, 2015), Appendix Table C5 also reports wild-cluster bootstrap p-values at both levels.[54] Under the city-level bootstrap, both investment measures remain significant ($p = 0.024$ and 0.025), and the pig-iron-to-crude-steel ratio is significant at the 10% level ($p = 0.063$). The sintering-to-crude-steel ratio is not statistically distinguishable from zero ($p = 0.203$), which is why we treat it as corroborating evidence. Province-level bootstrap p-values range from 0.172 to 0.371 across the six outcomes, which is unsurprising with only 12–14 province clusters. We report the province-level bootstrap as a stringent qualification; for city-assigned targets, the city-level bootstrap is the relevant benchmark.

Table C4: Robustness Checks: Province-Clustered Standard Errors

	(1)	(2)	(3)	(4)
Dependent variable	Pig iron/ crude steel	Sintering/ crude steel	Env. investment	Air investment
Units	Tons/ton	Tons/ton	10k 2015 CNY	10k 2015 CNY
Treatment	-0.076**	-0.166***	38,997**	36,089**
	(0.031)	(0.035)	(13,677)	(15,977)
Observations	389	364	338	320
R^2	0.800	0.800	0.584	0.575
Dep. var. mean	0.944	1.446	24,039	19,511
City controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes

Notes: Each column repeats the baseline estimate of Equation (2). Standard errors clustered at the province level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[54] Webb weights, 9,999 replications. Because the bootstrap routine does not support two absorbed fixed-effect sets, these models enter the fixed effects as explicit dummies, estimated on the same observations as the main tables.

Table C5: Alternative Inference: Wild Cluster Bootstrap

	(1) Coefficient	(2) SE	(3) Prov. cluster p	(4) Prov. wild p	(5) City cluster p	(6) City wild p
Pig iron / crude steel	-0.076*	(0.031)	0.029	0.371	0.020	0.063
Sintering / crude steel	-0.166	(0.099)	0.000	0.172	0.100	0.203
Env. investment (10k 2015 CNY)	38,997**	(13,677)	0.014	0.200	0.007	0.024
Air investment (10k 2015 CNY)	36,089**	(13,197)	0.043	0.216	0.010	0.025
Pre-tax profit per ton (2015 CNY)	243.4**	(35.3)	0.000	0.243	0.000	0.018
Main-business gross margin	6.710*	(1.414)	0.000	0.182	0.000	0.069

Notes: Each row takes the coefficient and city-clustered standard error of the baseline estimate in the main tables. Columns (3)–(6) report p-values with clustering by province (12–14 clusters) or by city (32–39 clusters), from conventional inference and from the wild cluster bootstrap (Webb weights, 9,999 replications). Stars reflect the city-level wild bootstrap p-value. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Firms with plants in several cities. The MIIT equipment records used for the electric-arc-furnace check list each firm's blast furnaces and converters by plant, which shows whether a CISA reporting entity spans several cities. Of the 66 matched firms, five operate BF–BOF plants in more than one city: Angang (Anshan and Bayuquan in Yingkou), Laigang (Laiwu and Qihe in Dezhou), Pinggang (Pingxiang and Jiujiang), Shaanxi Steel (Longmen in Hancheng and Hanzhong), and Shougang Group (Qian'an and Caofeidian in Tangshan, and Qinhuangdao). For these firms, a single target intensity measures the pressure on their plants with error. Appendix Table C6 addresses this in two ways. The second row drops the five firms. The third row keeps them and replaces each firm's target intensity with the average across its plant cities, weighted by each plant's share of the firm's blast-furnace volume in the 2012–2014 MIIT records. In both specifications, the pig-iron-to-crude-steel estimate and both investment estimates keep their signs and remain statistically significant; the sintering-to-crude-steel estimate keeps its sign but becomes imprecise.

Table C6: Firms with Plants in Several Cities

Dependent variable	(1) Pig iron/ crude steel	(2) Sintering/ crude steel	(3) Env. investment	(4) Air investment
Units	Tons/ton	Tons/ton	10k 2015 CNY	10k 2015 CNY
Baseline	-0.076**	-0.166*	38,997***	36,089***
	(0.031)	(0.099)	(13,677)	(13,197)
Observations	389	364	338	320
Excluding multi-city firms	-0.106***	-0.165	27,167**	20,872**
	(0.038)	(0.122)	(12,097)	(8,290)
Observations	345	320	291	272
Capacity-weighted target intensity	-0.074**	-0.117	39,252***	35,293**
	(0.031)	(0.116)	(13,720)	(13,213)
Observations	389	364	338	320
City controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes

Notes: Multi-city firms are the five firms whose MIIT equipment records list blast-furnace or basic-oxygen-furnace plants in more than one city (Angang, Laigang, Pinggang, Shaanxi Steel, and Shougang Group). The second row drops them. The third keeps them and assigns each the average target intensity of its plant cities, weighted by blast-furnace volume in the 2012–2014 MIIT records, while all other firms keep their baseline intensity. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

References

Cameron, A. C. and D. L. Miller (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources 50*(2), 317–372.

Appendix D: Per-Ton Accounting and Magnitude Checks

Per-ton accounting comparison. We examine whether the financial pattern has a cost-based counterpart. We divide operating cost and operating revenue by crude-steel output in the matched financial sample. Because the monetary numerators and physical output are both reported in units of 10,000, the ratios are CNY per ton; the monetary numerators are first converted to 2015 prices. Table D1 restricts the comparison to the 299 observations for which all four accounting outcomes are observed, winsorizes operating cost and revenue per ton at the 1st and 99th percentiles, and estimates the baseline specification. Columns (1) and (2) repeat columns (5) and (4) of Table 4; columns (3)–(4) add the operating revenue–cost spread per ton and source-reported pre-tax profit per ton on the same observations.

At one standard deviation of target intensity, operating cost per ton falls by 272 CNY and operating revenue per ton falls by 234 CNY, and the operating revenue–cost spread rises by 37 CNY per ton; none of these estimates is statistically significant under city clustering. Source-reported pre-tax profit per ton rises by a significant 65 CNY. The point estimates suggest improved performance, but the spread is not an accounting decomposition of pre-tax profit, since period expenses, financing costs, subsidies, taxes, and other items may also have changed. Because operating cost covers materials, energy, labor, maintenance, logistics, and more, the estimates show neither which component declines nor the effect of scrap substitution on any of them. All monetary magnitudes are in 2015 prices.

Table D1: Target Intensity and Per-Ton Operating-Cost Accounting

	(1)	(2)	(3)	(4)
Dependent variable	Operating cost/ crude-steel ton	Operating revenue/ crude-steel ton	Revenue–cost spread/ crude-steel ton	Pre-tax profit/ crude-steel ton
Units	2015 CNY	2015 CNY	2015 CNY	2015 CNY
Target intensity × Post	-902.664	-778.705	123.959	217.174***
	(625.735)	(700.334)	(123.466)	(29.537)
Observations	299	299	299	299
R^2	0.933	0.932	0.728	0.774
City controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes
Dep. var. mean	5,566	5,664	98.72	91.44

Notes: Each column reports a continuous difference-in-differences estimate from Equation (2) on the firm-years in which all four outcomes are observed. Operating cost and operating revenue per ton are winsorized at the 1st and 99th percentiles before the spread in column (3) is formed; the spread is not operating profit because it does not deduct period expenses or other items below operating cost. Column (4) is CISA's reported pre-tax profit per ton of crude steel. Standard errors clustered at the city level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Cost saving implied by the scrap-share increase. The observed 2.2-percentage-point increase in the converter scrap share implies a small direct saving when scrap is cheaper than hot metal. Using the metallic-balance yield of $\eta = 0.977$, the mechanical saving per ton of crude steel

is $\Delta\sigma(C^{HM} - P^S)/\eta$. In early 2017, an industry report using Mysteel quotations placed East-China heavy scrap at 1,800–1,850 CNY per ton and hot-metal cost at 2,300–2,400 CNY.[1] Dividing these 2017 quotations by the 2017 GDP deflator (2015=100) gives a scrap–hot-metal gap of about 430–570 CNY per ton in 2015 prices. Applied to the estimated share change, this is about 10–13 CNY per ton of crude steel in 2015 prices. That is directionally consistent with a cost channel but far smaller than the imprecisely estimated 272-CNY cost decline in Table D1.

The calculation applies to early-2017 prices only. Scrap and hot-metal prices vary materially, and the relative price can reverse; converter thermal-balance constraints also limit the feasible scrap share.[2] The market-price evidence makes a cost response plausible, and the imprecise accounting estimates show operating cost per ton falling more than operating revenue per ton in the matched sample. The evidence for a cost channel is therefore suggestive.

Back-of-the-envelope scale of abatement spending. A one-standard-deviation increase in target intensity is associated with about 117 million CNY more environmental investment per firm-year (Table 3). At the average crude-steel output of the firm-years in that regression, 6.6 million tons, this is roughly 18 CNY per ton of crude steel. The amount is of the same order as the 10–13 CNY per ton saved by the scrap-share increase at 2017 input prices and about one quarter of the 73 CNY increase in pre-tax profit per ton. The calculation compares magnitudes only. Investment enters profit through depreciation over the life of the equipment, the operating cost of abatement is not observed, and the benefits of the regulation depend on air quality and health outcomes outside our data.

Emission reduction implied by the scrap-share increase. We assess the potential magnitude of the SO_2 reduction associated with the observed input substitution, holding net emissions per ton of sinter constant. All pre-policy values below are computed from our sample for 2012–2015. A one-standard-deviation increase in target intensity is associated with approximately 0.023 fewer tons of pig iron per ton of crude steel. Applying the pre-policy ratio of 1.51 tons of sinter per ton of pig iron implies a reduction of approximately 0.034 tons of sinter per ton of crude steel. At the pre-policy net emission factor of 0.69 kg of SO_2 released per ton of sinter after end-of-pipe treatment, the implied reduction is approximately 0.024 kg of SO_2 per ton of crude steel, or 1.9% of the pre-policy mean of 1.22 kg.

Alternatively, applying the same emission factor directly to the estimated reduction of 0.050 tons of sinter per ton of crude steel gives approximately 0.035 kg of SO_2 per ton of crude steel, or 2.9% of its pre-policy mean. The two calculations use related production outcomes and should not be viewed as independent estimates. The emission factor is already measured net of treatment, so no further adjustment for desulfurization is needed.

These calculations describe the input-mix channel under a constant net emission factor; they do not identify the actual emissions response. They assume that the average net emissions factor approximates the marginal factor, abstract from firms' endogenous adjustments in desulfurization

[1] Mysteel is a Chinese bulk-commodity market-information and price-reporting platform: https://www.mysteel.com/. China Securities reports the quoted Mysteel price range (January 23, 2017): https://www.cs.com.cn/zzqh2020/201701/t20170123_5163513.html. For a discussion of the scrap-cost advantage created after the elimination of induction-furnace capacity, see Chinese Academy of Engineering: https://www.engineering.org.cn/sscae/CN/1160081088406151335.

[2] For example, a June 2020 China Economic Net report notes a period in which scrap cost exceeded hot-metal cost and discusses the thermal-balance constraint: https://www.ce.cn/cysc/ny/gdxw/202006/19/t20200619_35169109.shtml.

intensity, and inherit uncertainty from the production estimates and calibration parameters. In addition, national monitoring guidelines distinguish pollutant releases at discharge outlets from measurements at treatment-facility inlets (as discussed in Section 7.1). We do not observe the operating costs or removal efficiencies necessary to quantify any offsetting change in end-of-pipe treatment.