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Research Report

Reducing industrial pollution and inter-regional environmental inequality via the world's largest high-speed railway network

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Abstract

Industrial pollution and the associated spatial environmental inequality increase health risks and hinder sustainable development, particularly in low- and middle-income countries. Large-scale public transportation infrastructure that connects developed and developing cities, exemplified by high-speed railway (HSR), has the potential to be an effective instrument. Here, we provide nationwide micro-level estimates for the overall and distributional environmental impacts of HSR in a middle-income context. Using over half-a-million emission records of industrial firms during the rapid expansion of Chinese HSR, the world's largest HSR program, we find significant reductions in firm emissions after HSR opening (by 5.11–13.80%). The contributions come via facilitating intercity element flows like (green) technologies and lowering emission intensities. At the aggregate level, the HSR-driven emission reductions account for 0.49–1.70% of the overall emissions during the study period. Last, we examine the geographical distributional impacts of HSR. Both our between-city and within-city analyses reveal that laggard areas benefit more from HSR connection, thereby contributing to inter-regional environmental equality.

Keywords: transportation infrastructure, high-speed railway, industrial pollution, environmental inequality

Significance Statement

Low- and middle-income countries suffer more from industrial pollution and the associated spatial environmental inequality. Existing solutions rely on technological advancements, command-and-control regulations, and targeted governmental subsidies, which, however, could be time-consuming and costly or may not meet their initial goals. This study argues that large-scale intercity transportation program can be an effective alternative instrument. This research uses the Chinese HSR, the world's largest HSR program, as an example to test the effect. We find substantial reductions in industrial pollution after HSR connection. It is further shown that less-developed regions benefit more from HSR opening, thereby bridging the gap between developed and less-developed areas and helping to reduce inter-regional environmental inequality.

Introduction

The process of industrialization has exacerbated pollution and increased environmental health risks, with industrial pollution emerging as a major contributor (1). However, pollution and the associated environmental risks are not distributed evenly across space; Instead, pollution-related hazards disproportionately affect certain subgroups of populations and regions, resulting in spatial environmental inequality. Low- and middle-income areas, which are marginalized and with disadvantaged bargaining power, are exposed to higher environmental risks and suffer much more from the pollution-induced negative impacts (2–4). In the United States, areas with more low-income populations are at a higher risk of death from pollution (5). This phenomenon is even more pronounced in developing countries like China, where less-developed inland provinces and northeastern regions experience much higher pollution intensities and environmental health risks such as lung cancers and pollution-related deaths (6). The United Nations has sharpened calls to "ensure sustainable consumption and production patterns" (The 12th Sustainable Development Goal [SDG 12]) and "reduce inequality within and among countries" (SDG 10) (7). Therefore, there is an urgent need to find effective instruments to reduce industrial pollution

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and mitigate the associated spatial inequality. Despite the practical significance, insufficient academic attention has been paid to spatial environmental inequality, and effective instruments for addressing it are still lacking, particularly in developing economies.

We argue that large-scale intercity transportation network, exemplified by high-speed railway (HSR), is an effective instrument and provides a possibility (Supplementary Text Section S1). Such a large-scale transportation system bridges developed and developing areas, accelerating the spatial mobilities of capital, labor, technology, and information, and introducing more resources and opportunities to lagging regions (8–10). Late-comer areas could therefore update their (green) technologies and restructure production processes, playing an active role in lowering emissions of industrial pollutants. By doing so, late-comers could narrow the gap with first-movers and help mitigate spatial environmental inequality. In sum, HSR helps reduce industrial pollution and laggard areas could benefit more from HSR connection. While some policy instruments, which aim to promote green transition, could widen spatial inequalities (11), our proposed alternative instrument, HSR, could mitigate inequalities. In spite of its theoretically possible contributions, less research has been conducted to test the relationship and provide micro-level evaluations. Moreover, the extent to which HSR opening leads to reductions in industrial pollution, especially in underdeveloped cities, remains unclear.

Using data from over half a million records of industrial firms and the early expansion of HSR in China, this study provides the first nationwide micro-level estimates of the overall and distributional environmental impacts of HSR in a developing context. Compared with early-adopter countries such as Japan, France, Spain, and Germany, China is a middle-income country with huger spatial disparities. Despite these challenges, China has set an ambitious plan for building a large-scale HSR network, which aims to promote factor flows and reduce spatial inequalities (12). Our employed firm-level emission data cover the period from 1998 to 2010, which coincided with the first wave of HSR construction in China. The early expansion connected economically dense southeastern coastal regions, less-developed central inland provinces, and economically stagnant northeastern areas (Fig. S1). As of 2010, China had established the world's largest HSR network, surpassing the total mileage of major early-adopter countries, with an annual passenger volume of 290 million.

Our modeling results confirm a positive role of HSR in the reduction in industrial pollution and the mitigation of inter-regional environmental inequality. We find that the introduction of HSR reduces firm-level emissions of sulfur dioxide (SO_2), dust, wastewater, and chemical oxygen demand (COD) by 8.25%, 13.80, 5.11, and 11.88%, respectively. The reduction effects are more pronounced in cities with higher pollution intensities before HSR opening and strengthen over time. At the aggregate level, HSR connection results in a reduction of 0.82 million tons (Mt) of SO_2, 0.63 Mt of dust, 0.92 gigatons (Gt) of wastewater, and 0.43 Mt of COD, respectively, accounting for 0.49–1.70% of the national overall emissions in the industrial sector during that period. Higher aggregate reductions are found in underdeveloped areas like central inland provinces and northeastern regions, which provides preliminary evidence that HSR helps alleviate inter-regional environmental inequality. We next formally testify the validity of this conjecture, by exploring the geographical distributional impacts of HSR at various scales. Between-city analysis reveals that late-comer regions experience greater effects in stipulating (green) innovations, decreasing emissions and emission intensities. Within-city analysis shows that although the HSR-induced reduction effects attenuate by distance, late-comer areas enjoy higher spillover effects and larger buffers. Evidence from the micro-level inequality index, which is constructed to formally quantify environmental inequality, also supports this argument. Taken together, our multifaceted analyses indicate that HSR plays a significant and positive role in achieving inter-regional environmental equality.

We contribute to an important issue—spatial inequality—by zooming in on environmental inequality and its possible antidote in the developing world. Historically, the inequality literature mainly focused on economic inequality (e.g. income inequality), paying insufficient attention to environmental inequality (13). Given the pressing environmental burden, recent studies have shifted the research interests and examined environmental inequality in developed countries like United States, United Kingdom, and Germany (5, 14–16). However, we know little about it in the context of developing countries, which are more vulnerable and suffer more from inequalities. This paper fills in this gap, by investigating *whether* and *how* HSR contributes to spatial environmental inequality in China. We observe higher reductions in late-comer areas after connected to the HSR network. The contributions come via intercity element flows and intracity spillovers. Our findings are of importance and general interests, as China faces with huge spatial disparities and takes up more than one-fifth populations of the developing countries. Experiences in China could provide implications for other developing countries which seek to write successful "green stories."

This paper also speaks to an emerging literature of the environmental impacts of transportation infrastructure in general and HSR in particular. Existing research has investigated the environmental impacts of the substitution between railway and other types of transportations (17–19). Another strand of studies has explored the direct impacts on local environmental performance using aggregate data (20, 21). Few exceptions have provided micro-level evidence, but their analyses are based on specific industries or regions, whose external validities and generalities are of concern (18, 22). We extend it by presenting nationwide micro-level estimates in a developing context using detailed corporate emission records of major industrial pollutants for more than a decade.

Results

Industrial pollution and the associated spatial environmental inequality threaten sustainable development. We argue that HSR, a public transportation system that links developed and developing areas, could be an effective instrument for both reducing pollution and mitigating environmental inequality. In this section, we first explore the overall and heterogeneous impacts of HSR opening and investigate the underlying mechanisms and spillovers. Next, we evaluate the magnitude of HSR connection by quantifying the aggregate emission reductions. As we will see, lagging areas benefit more from the access to such public transportation network, implying the positive role of HSR in alleviating spatial inequality. In the last subsection, we formally evaluate HSR's distributional effects, testifying whether HSR contributes to environmental equality.

Impacts of HSR on firm industrial pollution

To assess the impacts of HSR on emissions, we construct fixed-effects panel models that account for city-level economic fundamentals, firm-level outputs, province-year fixed effects,

Table 1. Impacts of HSR connection on firm-level emissions.

Variables	(1) ln (SO_2 emission)	(2) ln (Dust emission)	(3) ln (Wastewater emission)	(4) ln (COD emission)
HSR	−0.0825[a]	−0.1380[a]	−0.0511[a]	−0.1188[a]
	(0.0120)	(0.0139)	(0.0114)	(0.0137)
lnGDPPC	−0.0442	0.0540	0.3180[a]	0.2874[a]
	(0.0301)	(0.0348)	(0.0291)	(0.0385)
GDP_Growth	−0.0078[a]	−0.0068[a]	−0.0052[a]	−0.0048[a]
	(0.0008)	(0.0009)	(0.0005)	(0.0007)
lnPOPDEN	−0.0136	−0.1086[a]	0.0233	0.0260
	(0.0276)	(0.0333)	(0.0309)	(0.0431)
lnOutput	0.1285[a]	0.1126[a]	0.1202[a]	0.1128[a]
	(0.0024)	(0.0025)	(0.0021)	(0.0025)
Constant	10.9069[a]	9.2905[a]	8.9177[a]	6.0231[a]
	(0.4334)	(0.5283)	(0.4306)	(0.4362)
Province-year FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Firm-level obs.	611,665	568,912	660,886	581,855
Adjusted R^2	0.8068	0.7693	0.8422	0.7878
Within R^2	0.0442	0.0380	0.0481	0.0292

[a]$P < 0.01$, [b]$P < 0.05$, [c]$P < 0.1$. Robust SEs are in parentheses, clustered at the firm level. Models in columns (1)–(4) are all estimated by the fixed-effects panel model of Eq. (1). City-level GDP per capita, GDP growth, population density, firm-level output, province-year FEs, and firm FEs are controlled in all regressions.

and firm fixed effects. This model specification partials out the interfering influences of economic outputs, smooths region-specific time trend (e.g. regional labor markets, marketization levels, local cultural norms, and place-based policies), and incorporates firm characteristics (e.g. firm norms and the initial emission intensities). Identification relies on within-firm variations (i.e. between-year variations within a firm), and thus, we can interpret the estimator of HSR opening as the treatment effect of the access to HSR network, which captures the differences of a firm's emissions before and after HSR connection.

Table 1 reports the baseline results. As shown, the adjusted *R*-squares range from 0.7693 to 0.8422, indicating that the employed models could explain 77–84% variations of the firm-level emissions. It is hard to capture and predict all the micro-level behaviors in a single statistical model due to unobserved factors and uncertainty, though, our regression performs well and shows great potential. Our method is well applicable to assess the micro-level environmental impacts of transportation infrastructures. Our results further reveal that, after HSR connection, emissions of SO_2, industrial dust, wastewater, and COD decrease by 8.25, 13.80, 5.11, and 11.88%, respectively. This finding is in line with our conjecture that a large-scale transportation system such as HSR could be a part of the solution to industrial pollution.

We then conduct a series of tests to gauge the robustness of the baseline results (see Supplementary Text Sections S2–S3 for details). First, we perform sensitivity tests that trim the top 2.5% and bottom 2.5% emission records for each year (Table S2). Second, we use an alternative definition of HSR opening in a given year (Table S3). Third, we consider alternative timespan of emission records and starting timing of HSR expansion in China (Tables S4–S5). Fourth, we include industry-year fixed effects to account for potential unobservable confounders at the industry level (Table S6). Fifth, the locations of HSR lines may not be random, which leads to differences between HSR-connected cities and nonconnected cities before opening. The preopening differences may interfere the estimation of HSR connections. We thus add city linear time trend into the model, to control for the time-varying between-city differences and ease the nonrandomness concern (23) (Table S7). Sixth, to further address the nonrandomness issue, we control for a set of HSR selection variables. The HSR construction may follow specific criteria, including topographic factors, economic potentials, and investment capacities. Consequently, gradient, altitude, initial population scale, initial fiscal condition of each city, and their interactions with year dummies are further added into models (Table S8). Seventh, we conduct 500 placebo tests with false HSR connections, by randomly reassigning the location and timing (Fig. S2 and Table S9). Last, we exploit both historical (i.e. historical railroad network in 1961) and geographical variations (i.e. slope) to construct an instrumental variable for HSR connection (Supplementary Text Section S3, Tables S10–S11). The results of the above tests reveal a similar and stable pattern, confirming HSR's positive effects in emission reductions. The robustness of our results is verified.

Furthermore, we analyze the heterogeneities, mechanisms, and spillovers. (i) Heterogeneity by initial pollution level: in this article, we seek for feasible instrument for pollution reduction and inequality mitigation. HSR would be an effective tool if high-pollution areas could benefit more. For evaluation, we calculate the city-level initial emission intensity for each pollutant before HSR opening and differentiate two types of treatment groups: HSR cities with high/low initial emission levels. The results reveal that, in most cases, cities with high initial pollution intensities experience greater reduction effects, suggesting that HSR is an effective instrument for environmental governance (Table S12). (ii) Heterogeneity by opening time: we construct a five-year time window to explore the temporal reduction pattern and find that the HSR-induced reduction effects, although with some fluctuations, strengthen over time (Fig. S3 and Table S13). (iii) Mechanisms for HSR-induced emission reductions: our regression results unearth two important channels. At the micro-level, HSR connections contribute to lowering firm-level emissions through reducing emission intensities (emissions/outputs) (Table S14). Additionally, at the macro-level, HSR stimulates (green) innovations in a city, as measured by the number of total granted (green) patents per capita of each city and the number of granted (green) invention patents per capita of each city (Tables S15–S16). (iv) Spillover effects among cities: we adopt a newly proposed spatial econometric modeling strategy, which can provide micro-level estimates, to explore the spillover effects (see Materials and methods). Here, we consider two types of spillovers: spillovers from HSR-connected cities to neighboring nonconnected cities and spillovers from HSR-connected cities to other neighboring

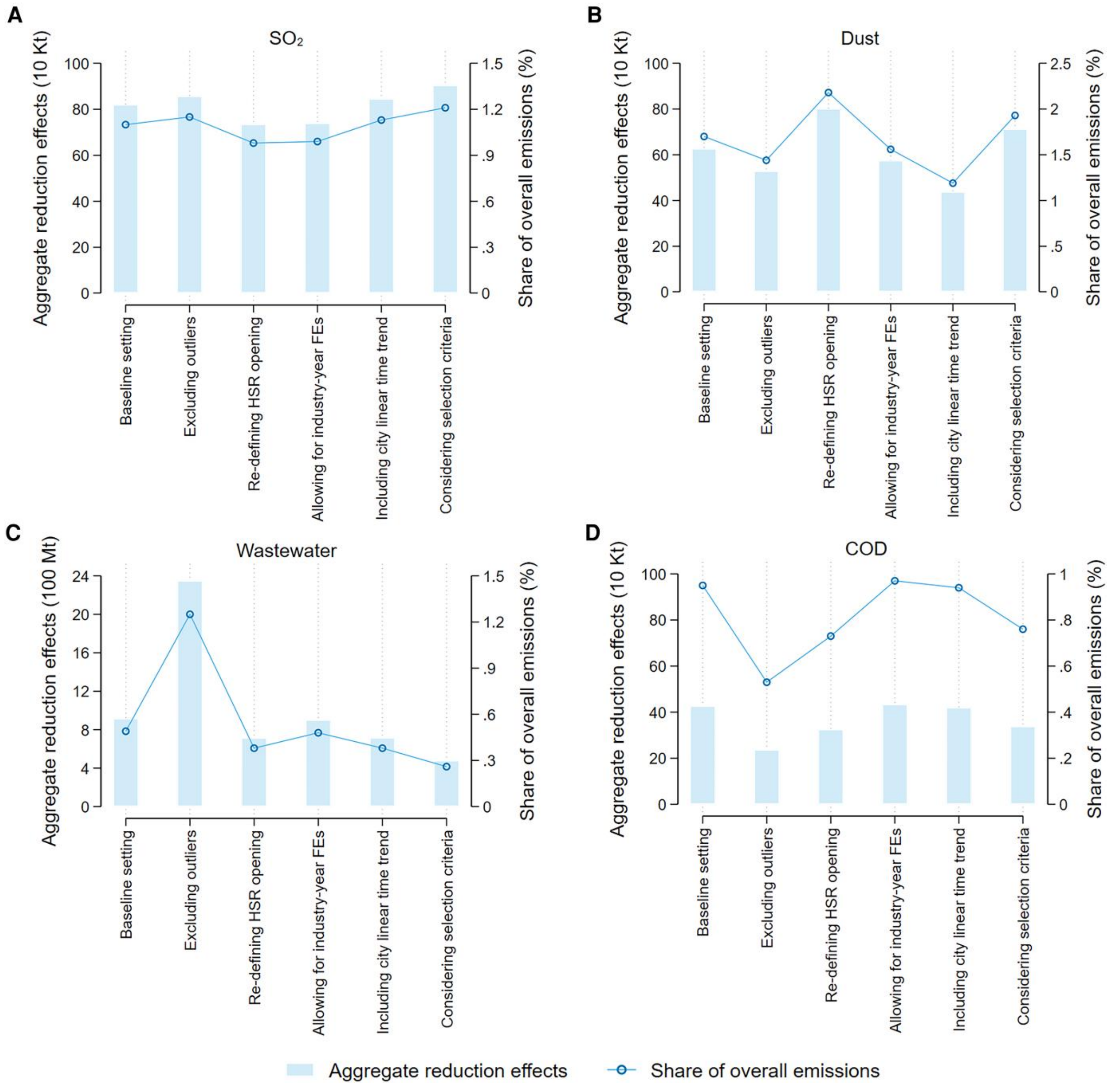

Fig. 1. National aggregate emission reductions by HSR connection. This figure plots the HSR-induced aggregate reduction effects and the share of the reductions to the overall emissions of the industrial sector during the whole study period. We consider four pollutants: SO_2 (A), dust (B), wastewater (C), and COD (D). We include six scenarios to quantify the HSR-induced reduction effects. The bars represent the aggregate reductions, while the hollow circles denote the proportions.

HSR-connected cities. We provide some evidence that those two spillover effects coexist. While HSR cities can lead to positive environmental externality to neighboring nonconnected cities, they may also result in negative spillovers to neighboring connected ones, arising competition effect (Table S17).

National- and city-level aggregate emission reductions by HSR connection

To understand the magnitude of HSR connection in environmental governance, we now turn to the aggregate reductions induced by HSR connection. By comparing the emission levels before and after HSR connections, we quantify the firm-level emission reductions and then aggregate to the national level. National aggregate effects are calculated for six scenarios, including baseline setting and alternative specifications (Supplementary Text Section S4). Figure 1 displays that, at the aggregate level, HSR connection leads to a reduction of 0.82 Mt of SO_2, 0.63 Mt of industrial dust, 0.92 Gt of wastewater, and 0.43 Mt of COD. The reduction effects account for 0.98–1.21%, 1.19–2.18%, 0.26–1.25%, and 0.53–0.97% of the overall emissions in China's industrial sector during the 13-year period. Using the baseline setting as a benchmark, HSR-induced reductions take up 1.10–1.70% of air pollution emissions and 0.49–0.95% of water pollution emissions. These findings indicate that the mitigation efforts are more evident in air pollution.

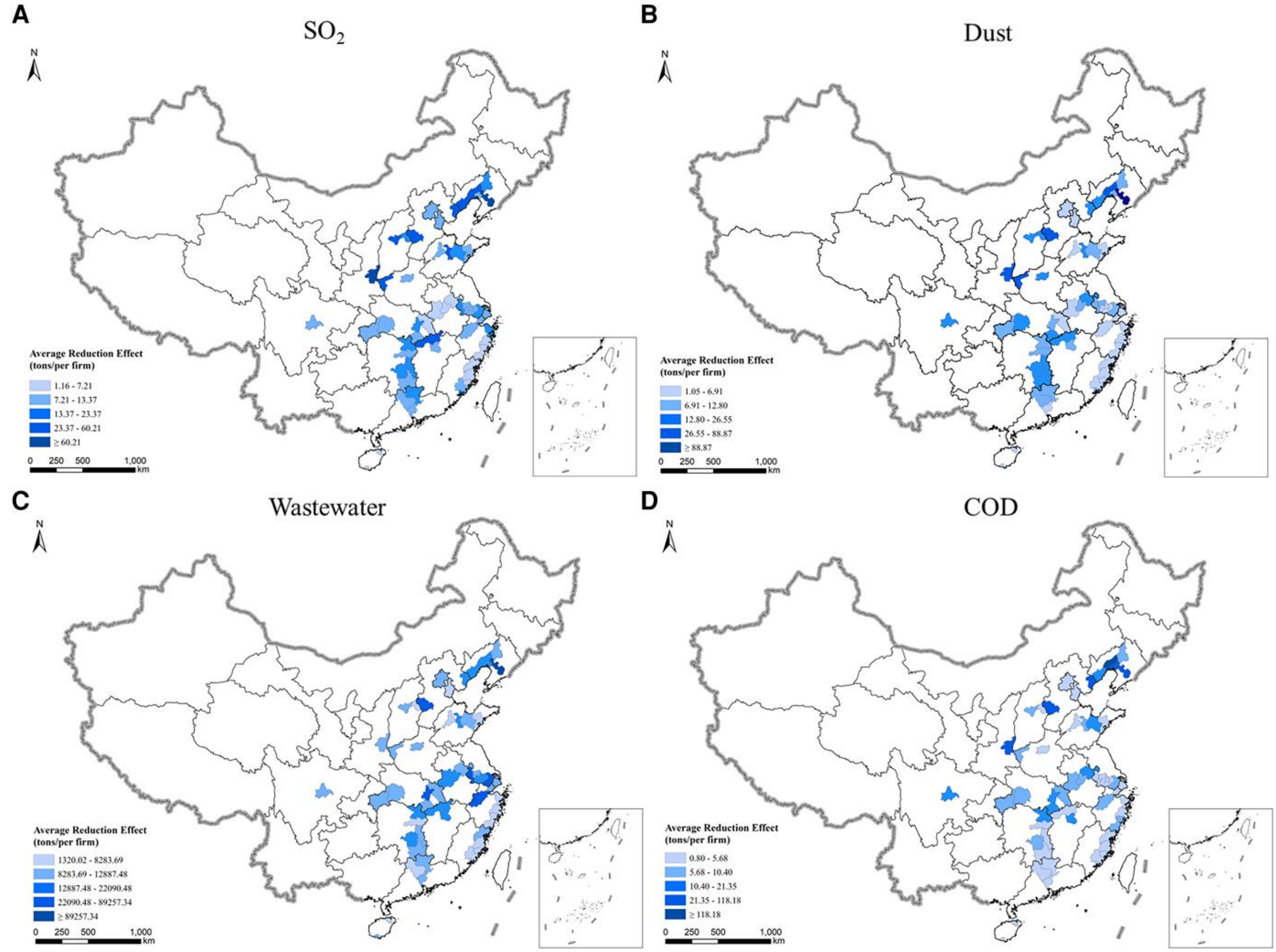

Fig. 2. City-level emission reductions by HSR connection. This figure displays the average reduction effects of HSR-connected cities. We consider four pollutants: SO_2 (A), dust (B), wastewater (C), and COD (D). We use the natural breaks method for classifications. The basic unit is "tons/per firm."

We then look into the city-level heterogeneity. Instead of a national aggregate investigation, we delve into the city-level granular analysis, calculating each connected city's average reduction effects. We use the benchmark estimates to quantify the city-level average reduction effects. The spatial pattern of the average reduction effect is mapped (Fig. 2), where the top 20 cities with the highest effect are listed in particular (Tables S18–S19). We discover a spatial pattern that northeastern regions and inland provinces experience a higher reduction effect from the HSR opening, averagely. Turning to the top 20 cities with highest average reduction effect, we find that half of the listed cities are located in northeastern provinces such as Liaoning (16 out of 80) and less-developed central provinces such as Hebei (8), Hubei (8), and Hunan (8). In particular, Anshan City, located in the Liaoning province, experiences the most significant reduction effects in both air and water pollutants. Anshan is an essential part of the well-known old industrial base of the Northeast China, which reached its peak during the planned economy era but has experienced stagnation in recent years. Heavy industry, especially the iron and steel industry, leads Anshan's economy, with industrial pollution being a significant concern. With access to such large-scale transportation network, Anshan and other similar underdeveloped cities are able to facilitate intercity element flows and communications. This enables them to attract more resources and opportunities, thereby restructuring local production processes and reducing industrial pollution. In sum, the city-level pattern suggests that cities in underdeveloped provinces experience higher average reduction effects from HSR connection. But it still renders further explorations.

Geographical distributional effects and inter-regional environmental inequality

Quantitative evaluations in previous subsections have suggested a distributional effect of HSR, providing preliminary evidence that laggard areas benefit more from accessing to the HSR network. In this part, we formally explore the geographical distributional effects of HSR, and more broadly, its role in the alleviation of spatial environmental inequality. We analyze the distributional impacts both at the between-city and within-city scales.

We first investigate the geographical distributional impacts at the between-city scale. While previous subsections have presented evidence that HSR reduces industrial pollution, which is partly driven by facilitating intercity element flows like technology and therefore lowering emission intensities, here we seek to explore whether late-comer regions could benefit more at these dimensions. We find that the HSR-induced effects are more evident and stronger in late-comer regions, which perform better

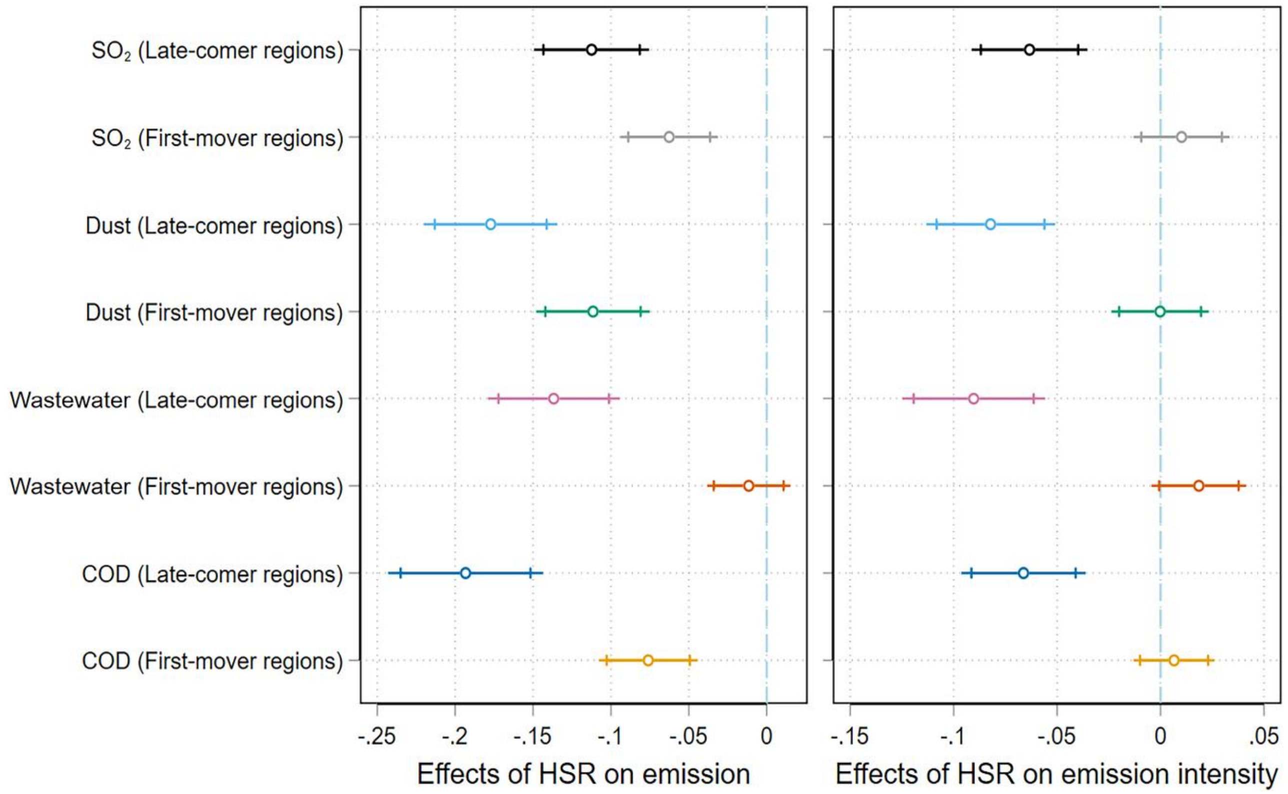

Fig. 3. HSR connection and firm-level emissions: between-city analysis. This figure plots the point estimates of HSR connection. Dependent variables are in log forms (*Y* axis), and samples are divided into "late-comer regions" and "first-mover regions" according to firms' geographical locations. The left sub-graph shows the impacts of HSR connection on firm-level emissions, while the right one plots the impacts on emission intensities. Detailed regression results are listed in Tables S20–S23.

in reducing emission intensities (Fig. 3), vitalizing (green) innovations (Tables S24–S25), and eventually lowering total emission levels (Fig. 3). In the post-1978 era, eastern coastal areas step ahead ("first-comer regions") than other provinces ("late-comer regions"), taking advantage of policy inclinations, locational proximities and the trend of globalization (24) (Supplementary Text Section S5). It broadens the gap between first-mover and late-comer areas, arising large spatial disparities. Besides economic disparity, inter-regional environmental inequality also exists, with late-comer provinces exposed to more severe pollution and higher environmental risks (25–27). We discover that such spatial environmental inequality can be mitigated by HSR. It is a large-scale transportation infrastructure program that spreads across the country, connecting both developed and underdeveloped cities. Under this scenario, late-comer regions "jump further" in upgrading technology, especially for green innovation, and reducing pollution intensity. Late-comer regions are therefore less exposed to environmental pollution.

Next, we downscale our analysis to the within-city level and present microgeographic evidence. We geolocate HSR stations and all industrial firms in our samples and then calculate the distance between a firm and its nearest HSR station within the same city. Six buffer rings are set to detect within-city spillovers, with one buffer consisting of a 10 km radius. Again, we split samples into first-mover and late-comer regions for regression analysis and test whether higher effects accrue to late-comer areas. We find that, compared with first-mover regions, late-comer areas are of larger buffers. Taking dust and COD for examples, while in first-movers the impacts of HSR connection could spill over to firms 30 km away, the impacted areas in late-comers are much larger, with an extra radius of 20 km or more. Second, it is also shown that in a given distance buffer, late-comer areas are of a higher reduction effect (Fig. 4). In general, our microgeographic evidence shows that late-comer areas benefit more from connecting to the HSR network. In laggard areas, HSR network spills over to larger areas and the reduction effect is greater in a given buffer ring, leading to greater positive environmental externality. Given that lagging areas suffer more from pollution than developed regions, these findings imply that HSR helps achieve spatial environmental equity, from the within-city perspective. These results illustrate HSR's role in improving spatial environmental justice at the within-city scale.

The former two analyses have offered many details for how HSR connection contributes to the mitigation of spatial environmental inequality. To provide more formal evidence, we construct a micro-level inequality index and estimate the impacts of HSR on spatial environmental inequality (see Materials and methods). The inequality index measures the differences between first-mover regions and late-comer regions' emission levels, and a smaller index indicates a lower level of spatial inequality. This index allows us to provide micro-level evaluations for whether HSR mitigates spatial inequality. We regress Eq. (11) for quantitative analysis. The results in Table 2 document a positive role of HSR in lowering inequality index and alleviating spatial environmental inequality (by 4.34–10.18%). This pattern prevails across all the four studied industrial pollutants, and the mitigation effects are more pronounced in water pollutants (by 6.74–10.18%), which relates to the huge spatial disparities in both water scarcity and water governance of China (28).

Taken together, we show that connecting to the HSR network helps reduce spatial environmental inequality, narrowing down

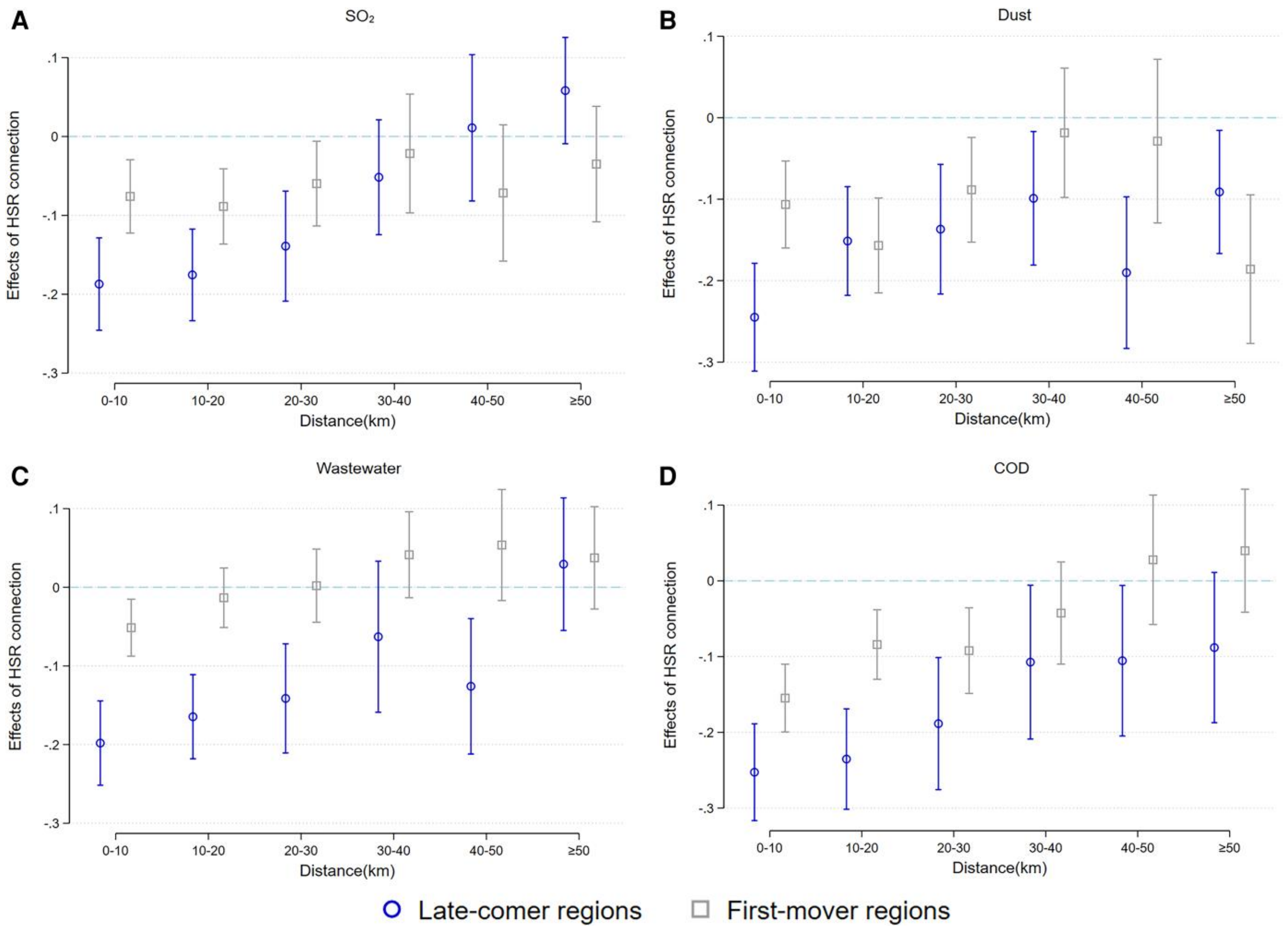

Fig. 4. HSR connection and firm-level emissions: within-city analysis. This figure shows the impacts of HSR connections on SO_2 emissions (A), dust emissions (B), wastewater emissions (C), and COD emissions (D), according to the distance between a firm and its nearest HSR station. We divide the full sample into two groups: first-mover regions and late-comer regions, and next estimate the results. Hollow circles and arms represent estimated coefficients of HSR and their 95% CIs in the case of late-comer regions, while squares and arms represent estimated coefficients of HSR and their 95% CIs in the case of first-mover regions. Detailed results are given in Tables S26–S27.

Table 2. HSR connection and inter-regional environmental inequality.

Variables	(1) ln (SO_2 environmental inequality)	(2) ln (Dust environmental inequality)	(3) ln (Wastewater environmental inequality)	(4) ln (COD environmental inequality)
HSR	−0.0434[a]	−0.0471[a]	−0.0674[a]	−0.1018[a]
	(0.0125)	(0.0140)	(0.0113)	(0.0119)
lnGDPPC	−0.0146	0.0469	0.2128[a]	0.1266[a]
	(0.0285)	(0.0321)	(0.0270)	(0.0310)
GDP_Growth	−0.0057[a]	−0.0035[a]	−0.0030[a]	−0.0053[a]
	(0.0007)	(0.0008)	(0.0006)	(0.0006)
lnPOPDEN	0.0699[a]	0.0650[a]	0.0591[a]	0.0613[a]
	(0.0021)	(0.0023)	(0.0018)	(0.0021)
lnOutput	0.0288	−0.1209[a]	−0.0245	−0.0447
	(0.0289)	(0.0339)	(0.0287)	(0.0352)
Constant	10.3215[a]	9.6977[a]	9.8583[a]	7.5575[a]
	(0.3891)	(0.5060)	(0.3340)	(0.3552)
Province-year FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Firm-level obs.	611,665	568,912	660,886	581,855
Adjusted R^2	0.6290	0.6053	0.7025	0.6744
Within R^2	0.0156	0.0194	0.0178	0.0202

[a]$P < 0.01$, [b]$P < 0.05$, [c]$P < 0.1$. Robust SEs are in parentheses, clustered at the firm level. Models in columns (1)–(4) are all estimated by the fixed-effects panel model of Eq. (11) in the “Materials and methods” section. City-level GDP per capita, GDP growth, population density, firm-level output, province-year FEs, and firm FEs are controlled in all the regressions.

the gap between late-comer and first-mover regions (as documented by the analysis for the inequality index). The contributions come via intercity element flows (as late-comer areas benefit more from facilitating element flows like [green] technologies and decreasing emission intensities, after connected to the HSR network) and intracity spillovers (as larger spillover effects of HSR are found in late-comer areas). In other words, underdeveloped areas are "jumping further" after HSR opening.

Discussion

Exploiting detailed emission records of industrial firms that cover 0.56–0.66 million firm-level samples and takes up 85% of the emissions in China's industrial sector, we deliver micro-level quantitative evidence that HSR connection lowers industrial pollution emissions. More specifically, HSR opening reduces SO_2, dust, wastewater, and COD emissions by 8.25, 13.80, 5.11, and 11.88%, respectively. At the national level, HSR-induced reductions aggregate to 0.82 Mt (SO_2), 0.63 Mt (dust), 0.92 Gt (wastewater), and 0.43 Mt (COD), accounting for 0.49–1.70% of the national overall emissions in the industrial sector during that 13-year period. Last, we investigate the geographical distributional impacts, by exploring whether and how HSR contributes to mitigating spatial environmental inequality. Our between-city and within-city analyses both reveal that underdeveloped cities benefit more from accessing to the HSR network, thereby helping achieving spatial environmental equity. This paper points out the environmental values of HSR. It presents multidimensional micro-level evidence that large-scale transportation networks, exemplified by the rapid expansion of Chinese HSR, are feasible instruments for both pollution reductions and inequality mitigations.

In the field of regional inequality, major research focus falls within income inequality, whereas environmental inequality attracts insufficient attention (29). Severe pollution hinders labor productivity, impairs physical health, lowers happiness, and increases mortality rate (30–32), especially for low-income populations or in low-income areas, arising inequalities among populations and regions (3, 33). It is necessary and urgent to seek for antidotes to spatial environmental inequality, de-trapping late-comer areas from environmental pollution and the associated inequality. This article contributes to this pivotal issue, by showing that, HSR construction, a large-scale and government-led transportation infrastructure program, can provide a possibility. Regression results reveal that late-comer regions benefit more from HSR connection—those regions experience stronger effects in incentivizing city-level (green) innovations, reducing firm-level pollution intensities, and thereafter decreasing firm-level emissions. In that scenario, less-developed areas are less exposed to environmental pollution. To conclude, HSR connection helps with mitigating spatial environmental inequality.

Our article could provide important implications for countries outside of China, particularly those developing ones which face with pressing environmental burdens and huge spatial disparities. Many developing countries have employed inter-regional transportation infrastructures as a key policy tool to promote regional development (34–36). However, the policy priority of these transportation programs often falls within developed areas and economic outcomes, while underdeveloped areas and environmental performance are given less attention. Our results, which are based on detailed analyses in a developing economy, imply that policy-makers should focus more on the latter two objects. We confirm that the environmental values of transportation infrastructures can be large, and lagging areas can "jump further" and "catch up" once connected to the transportation network. The environmental effects of inter-regional transportation infrastructures, both the overall and distributional effects, should be seen and carefully factored into future transportation planning and regional development strategy.

A limitation of this research lies in data availability. Although the dataset contains more than half a million firm-level emission records, we only focus on Chinese samples. With cross-country large-scale firm-level dataset, it would be useful to conduct solid cross-country analyses and evaluate the HSR-induced reduction effect in various economies with different institutional background. Following such idea, we can examine whether HSR mitigates environmental inequality at a global scale. Second, in this paper, we exploit a 13-year dataset for investigation, which could reflect HSR's short- and medium-term effects. When firm-level data with longer period are possible, we may capture and detect the long-run effects. These constrains in turn open up possible avenues for future research.

Materials and methods

Data

Firm-level data

Firm-level pollution data are from the Pollution Emissions of Industrial Firms (PEIF), collected and monitored by the Ministry of Environmental Protection of China (MEP). The PEIF database covers around 85% of the industrial pollution in China, containing records of emissions of major industrial pollutants (including SO_2, COD, wastewater and dust), outputs, basic information like names of firms, industrial codes, and geographical locations at the district level. Our sample period lasts from 1998 to 2010 (but we will extend it to 2012 in robustness checks). Annually, firms self-report their emission records of major pollutants to environmental protection bureaus (EPB) at the local level. Such data are then compiled by local EPBs and sent to MEP after careful verifications. As stated in the Environmental Protection Law, emission records in the PEIF data should not be used as the evidence for penalizing polluting firms, and therefore, those firms have little incentive to manipulate or misreport the data. Furthermore, local EPBs, usually the county-level ones, would cross-check the emission records and conduct on-site verifications. Provincial EPBs and MEP would also conduct unannounced field inspections, to avoid potential collusion between local EPBs and firms, and further verify the data accuracy (37–39). The PEIF database thus provides a unique, reliable, and comprehensive firm-level data source to study industrial pollution. Precise locational information of the industrial firms is not included in the PEIF dataset. We obtain the longitude and latitude of each industrial firm in the PEIF database from the Open Platform of Baidu Map (https://lbsyun.baidu.com/). Panel A in Table S1 reports the firm-level summary descriptions.

HSR data

We collect the opening dates of HSR lines and stations from the *China Railway Yearbook* and online official news. Information on the HSR stations is further verified using the official railway service website (https://www.12306.cn), which provides information on cities connected by the HSR network. We geocode the locations of HSR stations from the Open Platform of Baidu Map (https://lbsyun.baidu.com/).

Other city-level characteristics

City-level economic fundamentals, including annual GDP growth, GDP per capita, and population density, are collected from the

China's City Statistical Yearbooks. Patent data, including patent per capita and green patent per capita, are derived from the Chinese Intellectual Property Office (https://www.cnipa.gov.cn/col/col61/index.html). The dataset covers all micro-level patent data of China since 1985. We focus on granted patents rather than patent applications, because an application does not guarantee an approval by the intellectual bureaus, and it is better to use granted patents to reflect the innovation capability of a city. Here, we consider four types of granted patents: total granted patents, total granted green patents, granted invention patents, and granted green invention patents. To test the HSR-induced innovation effect in the mechanism analysis, we aggregate the patent data to the city level, standardized by the population. The classification of green patent is retrieved from the International Patent Classification Green Inventory, proposed by the World Intellectual Property Organization in 2010. We summarize the city-level characteristics in Table S1 (Panel B).

Models

Baseline model

We employ the following fixed-effects panel model to examine the relationship between HSR connection and firm-level emissions:

$$\ln(\text{Emission}_{icth}) = \alpha + \beta \text{HSR}_{ct} + \gamma X_{ct} + \delta X_{ict} + \zeta_{pt} + \eta_i + \varepsilon_{icth} \quad (1)$$

where i, c, t, and h denote firm, city, year, and the type of emission, respectively. The dependent variable is the logarithm of the emission level of h (SO_2, dust, wastewater, or COD) for firm i at city c in year t. HSR_{ct}, the key independent variable of interest, is a dummy, which equals 1 if city c in year t has been connected by HSR, and 0 otherwise. X_{ct} includes the city-level economic fundamentals, GDP per capita (*yuan*/person), annual GDP growth (%), and population density (persons/kilometer square) of city c in year t. X_{ict} controls the firm-level output in year t. ζ_{pt} denotes province-year fixed effects, while η_i represents firm fixed effects. Eventually, ε_{icth} is the error term of the model. Robust SEs are clustered at the firm level. Note that firm FEs are more general than city FEs; in other words, firm FEs cover city FEs. The effects of some city-level geographical factors (like climate and topography) and cultural factors, which rarely change in the short- or medium-period, are controlled with the inclusion of firm FEs.

City-level estimation

In mechanism analysis, we identify two important channels of how HSR poses influences on firm emissions, that is, firm-level pollution intensity (micro-level) and city-level innovation (macro-level). To explore the macro-level channel, we conduct the following city-level fixed-effects panel model:

$$Y_{ctk} = \alpha + \beta \text{HSR}_{ct} + \gamma X_{ct} + \delta X_{ct} + \theta_t + \rho_c + \varepsilon_{ictk} \quad (2)$$

where k indicates the type of dependent variables, patent per capita or green patent per capita of city c in year t. X_{ct} includes city-level economic fundamentals: annual GDP growth, GDP per capital, and population density. θ_t denotes time FEs. ρ_c represents city FEs. ε_{ictk} is the error term. Other signs or variable(s) (like HSR) are the same as in Eq. (1).

Between-city spillover estimation

We seek to provide some evidence for whether HSR connection can spill over to neighboring cities. We adopt a newly proposed spatial econometric modeling strategy to explore the between-city spillovers (40, 41). Such technique can provide micro-level estimators and consider different spillover effects. Specifically, the model can estimate the following two types of spillovers: spillovers from HSR-connected cities to neighboring nonconnected cities (from treated to untreated ones) and spillovers from HSR-connected cities to other neighboring HSR-connected cities (from treated to treated ones). This modeling strategy can offer more implications than a single spillover term. The model specification is as follows:

$$\ln(\text{Emission}_{icth}) = \alpha + \beta_1 \text{HSR}_{ct} + \beta_2 \text{SpilloverTNT}_{ct} + \beta_3 \text{SpilloverTT}_{ct} + \gamma X_{ct} + \delta X_{ict} + \zeta_{pt} + \eta_i + \varepsilon_{icth} \quad (3)$$

where SpilloverTNT_{ct} refers to the first type of spillover effect (i.e. spillovers from treated to untreated ones), which is defined as the share of connected cities in a city's neighborhood if such city had *not* been connected to the HSR network by t, and 0 otherwise. SpilloverTT_{ct} represents the second type of spillover effect (i.e. spillovers from treated to treated ones), which is defined as the share of connected cities in a city's neighborhood if such city had been connected to the HSR network by t, and 0 otherwise. Other settings are kept the same as in Eq. (1).

For a given nonconnected city c, it may receive one effect: spillover effect from HSR-connected cities in c's neighborhood. Likewise, for a given HSR-connected city c', it may receive two effects: direct effect of HSR connection, and spillover effect from other HSR-connected cities in its neighborhood (in most cases, a HSR line would link several cities; therefore, once a city has been connected to the HSR network, there would be other HSR-connected cities in its neighborhood). β_1 captures the direct effect of HSR opening, while β_2 and β_3 estimate the spillover effects. A negative (positive) and significant estimator of β_2 implies the presence of diffusion effect (siphon effect), while a negative (positive) and significant estimator of β_3 suggests that synergy effect (competition effect) may exist.

Microgeographic estimation

To provide microgeographic evidence for HSR's role in mitigating spatial environmental inequality, we investigate HSR's spillover effects within a city. To this end, we reconstruct the model in Eq. (1) as follows:

$$\ln(\text{Emission}_{icth}) = \alpha + \sum_{m=1}^{5} \beta_m \text{HSR}_{ct} \times D_{ictm} + \gamma X_{ct} + \delta X_{ict} + \zeta_{pt} + \eta_i + \varepsilon_{icth} \quad (4)$$

where m denotes the distance buffer between firm i and its nearest HSR station in city c (0–10 km, 10–20 km, 20–30 km, 40–50 km, 50 km above). D_{ictm} is an indicator variable, which takes the value of 1 if firm i is located within the buffer m, and 0 otherwise. Other variables and FEs remain the same as in Eq. (1).

Aggregate reduction calculation

The calculation of aggregate effect consists of three major steps. We first remove samples of city c which had not been connected by HSR during 1998–2010, the study period of our study.

In the second step, we calculate the average emission level of firm i from 1998 to 1 year before HSR connection and then multiply it with the coefficients estimated by Eq. (1) to calculate the firm-level emission reduction induced by HSR opening:

$$\text{Reduction}_{ich} = -(\hat{\beta}_h \times \overline{\text{Emission}}_{ich,t0-t1}) \quad (5)$$

where $\hat{\beta}_h$ is the coefficient for HSR connection estimated by Eq. (1), $\overline{\text{Emission}}_{ich,\,t0-t1}$ refers to the average emission of firm i, $t0$ is the starting year of our study, 1998, and $t1$ denotes the year before

HSR opening. For readability, we turn the value into positive.

Moving one stage further, we aggregate the firm-level reduction to the national level:

$$\text{Reduction}_h^{\text{Aggregate}} = \sum_{i=1}^{n} \text{Reduction}_{ich} \tag{6}$$

Inequality index and spatial environmental inequality

Inequality index

This paper aims to provide micro-level evaluations for the environmental effectiveness of HSR, including its role in mitigating spatial inequality. We therefore seek to construct a micro-level inequality index. The intuition is that, given two regions *a* and *b* (i.e. first-mover and late-comer regions; each region consists of a certain number of provinces/cities), we first calculate the annual medians for *a* and *b* and next quantify the difference between each firm *i* located in *a* (or *b*) and the median for *b* (or *a*). For a single firm, such difference measures the deviation between the firm *i* in region *a* (or *b*) and the average emission level in region *b* (or *a*). Higher deviation indicates a bigger gap and greater inequality between first-mover and late-comer regions.

First, we calculate first-mover region's and late-comer region's annual medians of emissions for all the studied industrial pollutants:

$$\text{Emission}_{ht,a}^{\text{Median}} \tag{7}$$

$$\text{Emission}_{ht,b}^{\text{Median}} \tag{8}$$

where *h* and *t* denote the type of pollutants and year, respectively. Furthermore, *a* represents the first-mover region, while *b* refers to the late-comer region. Equation (7) measures the annual medians of the emission levels for all industrial firms in the first-mover provinces. That is to say, we calculate the median value for all samples in the first-mover provinces in a given year. Similarly, Eq. (8) quantifies the annual medians for late-comer provinces.

Second, we calculate the difference between a firm's emission level in region *a* (or *b*) and the median emission level in region *b* (or *a*). For firms located in the first-mover region (region *a*):

$$\text{Inequality}_{icth} = \left|\text{Emission}_{icth} - \text{Emission}_{ht,b}^{\text{Median}}\right| \tag{9}$$

Similarly, the micro-level inequality index for firms in the late-comer region (region *b*) is given as:

$$\text{Inequality}_{icth} = \left|\text{Emission}_{icth} - \text{Emission}_{ht,a}^{\text{Median}}\right| \tag{10}$$

where Inequality_{icth} and Emission_{icth} are the firm-level inequality index and emission level, respectively. Other variables and notations are mentioned in Eqs. (1), (7), and (8).

Regression analysis

Eventually, we construct the following fixed-effects panel model to evaluate the impacts of HSR on spatial environmental inequality:

$$\ln(\text{Inequality}_{icth}) = \alpha + \beta \text{HSR}_{ct} + \gamma X_{ct} + \delta X_{ict} + \zeta_{pt} + \eta_i + \varepsilon_{icth} \tag{11}$$

where $\ln(\text{Inequality}_{icth})$ is the logarithm of the inequality index. We take a log form so that the estimated coefficients can be interpreted as elasticity estimators. Other variables and notations are kept the same as in Eq. (1).

Supplementary Material

Supplementary material is available at *PNAS Nexus* online.

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Author Contributions

Z.L., S.Z., and C.H. conceptualized the study and contributed to the writing of the manuscript. Z.L. constructed the dataset and carried out the statistical analysis under the guidance of S.Z.

Data Availability

The firm-level pollution and economic data are compiled by the Ministry of Ecology and Environment of China. Those data are provided under a nondisclosure agreement for the current study and are not publicly available. Those who are interested in the firm-level data may contact EPSDATA for access by request: https://www.epsnet.com.cn/index.html#/Index. HSR data can be obtained by request: https://oversea.cnki.net/KNavi/YearbookDetail?pcode=CYFD&pykm=YZGTD&bh=&uniplatform=OVERSEA&language=en. City-level socioeconomic data can be obtained by request: https://oversea.cnki.net/KNavi/YearbookDetail?pcode=CYFD&pykm=YZGCA&bh=&uniplatform=OVERSEA&language=en.

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